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The US Banks' Balance-Sheet Transmission Channel of Oil Price Shocks*

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Abstract

We document the existence of a quantitative relevant banks' balance-sheet transmission channel of oil price shocks by estimating a dynamic stochastic general equilibrium model with banking and oil sectors. The associated amplification mechanism implies that those shocks explain a non-negligible share of US GDP growth fluctuations, up to 17 percent, instead of 6 percent absent the banking sector. Also, they mitigated the severity of the Great Recession's trough. GDP growth would have been 2.48 percentage points more negative in 2008Q4 without the beneficial effect of low oil prices. The estimate without the banking sector is only 1.30 percentage points.

Keywords: Oil price shocks, DSGE models, Financial frictions

JEL classification: E32, E44, Q35, Q43

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1 Introduction

Oil price fluctuations have attracted a lot of attention in academia and in the policy arena since the 1970s. The amount of work since then has been impressive, and a large variety of issues have been covered. The identification of the causes and sources of oil price fluctuations and the relationship between oil price movements and the macroeconomy are among the most relevant. The list of issues is very long, and we refer the reader to Kilian (2008, 2014), Kilian (2014), Kallis and Sager (2017), Herrera et al. (2019), Bachmeier and Plante (2019), and Lang and Auer (2020) for extended reviews.

For the sake of our analysis, it is worth stressing that researchers have been proposing and analyzing many different direct and indirect channels through which oil price shocks can transmit to the macroeconomy, in particular the economies of oil-importing countries such as the US,[1] including, among others, the input-cost channel (Kim and Loungani, 1992, Backus and Crucini, 2000), the imperfect competition channel through large and time-varying markups (Rotemberg and Woodford, 1996), the capital-energy complementarities in production channel (Atkeson and Kehoe, 1999), and the energy channel through capital utilization and capital stock (Finn, 2000). Moreover, Hamilton (2008) highlights the disruption in consumers' and firms' spending on goods and services other than energy.[2] Other channels are the capital and labor reallocation channel (Hamilton, 1988, Bresnahan and Ramey, 1993, and Edelstein and Kilian, 2009), and the systematic monetary policy response channel (Bernanke et al., 1997).

Despite the ample effort devoted to identifying the relevant channels, surprisingly very little attention has been given to financial channels, especially to the effects that oil price shocks can have on banks' balance sheets and to the role that the banking sector can play in transmitting oil price shocks to the real economy. Anecdotal evidence suggests that low oil prices can favor banks as is the case for consumption, investments, and GDP growth.

[1] According to data from the US Energy Information Administration, the US shifted from being a net oil importer to being a net oil exporter in 2020 for the first time since 1949.

[2] That can happen through the discretionary income effect, or the uncertainty effect (Bernanke, 1983), or the precautionary saving effect, or the operating cost effect.

For instance, some Moody's credit outlook reports stress that "lower oil prices will broadly support bank creditworthiness [and they] are positive for the operating environment of US banks".[3] More formal empirical evidence also indirectly suggests the same. The inverse link between oil prices and the stock market is well established in the literature, e.g., Kilian and Park (2009) and Aastveit (2014). Since the same evidence suggests that banks' stock market indexes behave accordingly, that means that low oil prices have positive effects on banks' net worth (and vice-versa). More recently, Abbritti et al. (2020) find that a lower oil price tends to be associated with decreased credit spreads, which in turn might be explained by a less risky financial system or, equivalently, by a healthier banking sector.

Both the anecdotal and the empirical evidence highlight one key fact: oil price shocks affect banks' balance sheets pro-cyclically. And, as the financial accelerator theory postulates, pro-cyclical variations in intermediaries' balance sheets can be at the core of amplification mechanisms that amplify the effect of those shocks, giving the banking sector a potential role in characterizing how those shocks transmit to the real economy and how relevant they are in explaining business cycle fluctuations. In this paper, we formalize those ideas and we provide a framework that: 1) can rationalize the single pieces of empirical evidence about oil and banks described above, together with what the literature has agreed to be the effects of oil price shocks on the real economy, i.e., low oil prices are beneficial for the real economy and vice-versa; 2) can account for the accelerator effect.

To do that, we set up a real business cycle dynamic stochastic general equilibrium (DSGE) model with a banking sector, mainly based on the endogenously determined banks' balance sheet constraints framework as in Gertler and Karadi (2011), and an oil sector that accounts for the different sources of oil price shocks, in line with Bjornland et al. (2018). We incorporate a direct channel of oil price shocks in assuming that oil enters the production function as an intermediate input. The banking sector provides an indirect financial channel.[4] Then, we estimate the model using real and financial US data and oil data for the period 1992Q1-2019Q4.

[3] See Moody (2015b), Moody (2015c), and Moody (2015a).

[4] We define it as an indirect channel because the accelerator that triggers it is due to second round effects.

Our contribution is manifold. First, we flesh out the theoretical banks' balance sheet transmission channel of oil price shocks that has been neither proposed nor formalized in the literature. Second, thanks to our estimated model, we evaluate that channel empirically and we test its relevance. Third, we shed light on how the presence of the banking sector helps to characterize the quantitative importance of oil price shocks for the US economy through the entire sample, and during particularly interesting events such as the Great Recession. Fourth, we offer a business cycle accounting in a model the features a meaningful number of real, financial, and oil shocks.

In more granular detail, the indirect financial channel we propose and test is based on the financial accelerator mechanism embedded in the banking sector of Gertler and Karadi (2011). It is supposed to amplify the effects of an oil price shock on the US economy, initially hit through the direct channel in our model. In a nutshell, it works as follows: if the price of oil increases, firms reduce the amount of oil used as an input and they cut production. That leads to a reduction in investments and in turn to a lower demand for capital. As a result, the price of capital drops. Given that the asset side of banks' balance sheet is evaluated at the price of capital (claims on firms are claims on banks), banks' financial position deteriorates, leading to a disruption in borrowing and lending. This pushes up the firms' borrowing costs through an increase in the credit spread. Firms reduce the demand for capital even further, invest less, and the economy suffers an even bigger recession. We find that the accelerator mechanism is present and it is statistically significant, meaning that variables react statistically more to an oil price shock in our baseline model than in a model without a financial sector.

The strategy of evaluating the relevance of oil price shocks based on their impact on GDP (either through impulse response functions or by estimating its elasticity) or other macro-aggregates is common in the literature. However, this does not give a complete picture of the overall importance of oil price shocks. We rely on the variance decomposition to assess the contribution of shocks to the variability of GDP growth, and on the historical shock decomposition to study the evolution over time of their contribution to the real economy.

The former highlights that in our baseline model, oil price shocks account for a non-negligible share of GDP growth variability, up to 17 percent in the very short run and 13 percent in the medium and long run. In a model without banking, that share would be reduced to a more modest 6-7 percent across different horizons, in line with the general idea that oil price shocks cannot be a relevant source of business cycle fluctuations if the input-cost channel is the only one at play (see, for instance, Rebelo, 2005, Hamilton, 2008, and Kilian, 2014). The historical decomposition suggests that oil price shocks played a beneficial role in the Great Recession's trough, meaning that the trough would have been a lot more negative in the absence of positive oil price shocks.[5] The beneficial effect would have been about half the size in the model without banking.

Finally, to quantify how much oil prices affected the economy during the Great Recession, we run a counterfactual experiment. We feed the baseline model with all estimated shocks, but the oil price one. We show that per capita quarter-on-quarter real GDP growth would have been 2.48 percentage points more negative in 2008Q4 without the beneficial effect of low oil price. On the contrary, a model without the banking sector estimates a lower beneficial effect of only 1.30 percentage points.

All of our results highlight the fact that the financial channel we analyze is key to better characterizing the relevance of oil price shocks. Not considering the effect of the amplification mechanism inherent in the banking sector would lead to greatly underestimating the effect of oil price shocks on the economy. This is highly in line with the literature investigating the role of indirect channels which claims that oil price shocks influence economic activities beyond that explained by direct input-cost effects (see e.g., Davis and Haltiwanger, 2001, Lee and Ni, 2002, Ramey and Vine, 2010, and the references therein).

The paper is structured as follows. In the next subsection we review the relevant literature. We then describe our baseline model. We then present the estimation details, our results, and a series of robustness tests, before offering concluding remarks.

[5] From 2008Q3 to 2008Q4, the real oil price fell by approximately 50 percent. Between the last quarter of 2008 and the second quarter of 2009, the price of oil was below $60 per barrel in nominal terms.

1.1 Literature Review

As stressed in the Introduction, it is somewhat cumbersome to provide an extensive review of the huge literature on oil price shocks. In this section, we provide a non-exhaustive review of the papers that are mostly related to our analysis, i.e., those that deal with the effects of oil price shocks on US GDP, those that analyze the relationship between the price of oil and stock prices, those that analyze the relationship between the price of oil and the banking sector, and those that include oil prices in a DSGE framework.

The first strand of the literature to which our paper is related is the one investigating the effects of oil price shocks on US GDP. Many empirical studies have found a negative relationship between oil prices and US aggregate economic activity (see, for example, Loungani, 1986; Mork, 1989; Lee et al., 1995; Balke et al., 2002). More recently, a growing literature has focused on the consequences of oil price fluctuations that arise from different sources in the oil market. Some studies, such as Kilian (2009, 2014), Kilian and Vigfusson (2011), and Kilian and Murphy (2012, 2014) provide evidence that oil price changes that arise from demand shocks in the oil market have the largest effects on the real oil price. Subsequently, other contributions, like Baumeister and Peersman (2013), Baumeister and Hamilton (2019), and Caldara et al. (2019), have found that oil supply shocks are as important as or even more important than demand shocks. Very recently, Kilian (forthcoming) and Kilian and Zhou (forthcoming) cast doubt on those findings about oil supply shocks and support the view that oil demand shocks are the dominant driver of the real price of oil.

The second strand of the literature that we focus on is the one analyzing the relationship between the price of oil and stock prices. In the previous section, we mentioned the study by Kilian and Park (2009) that assesses the response of US real stock returns to different sources of oil price shocks. The work by Kilian and Park (2009) represents a sort of turning point for the analysis on this topic. Studies before that paper could not find a consensus about the relationship between stock prices and the price of oil. For instance, Kling (1985) found a negative relationship between changes in the price of oil and the stock market. On the other hand, Chen et al. (1986) found that changes in the price of oil had no effect on asset prices. The findings by Jones and Kaul (1996) indicated a negative relationship between stock returns and changes in the price of oil futures. Similarly, Sadorsky (1999) found that positive shocks to oil prices depress real stock returns.

Studies after the paper by Kilian and Park (2009) have focused on more detailed aspects of the relationship between oil price shocks and the US stock market. Some studies have focused on the time-varying nature of the correlations between oil price shocks and stock returns (see, for example, Broadstock and Filis, 2014). Other papers have analyzed the asymmetric responses of the US stock market to oil price shocks (see, for example, Alsalman and Herrera, 2015). Some other studies have also assessed the volatility spillovers between oil and stock markets (see, among others, Souček and Todorova, 2013 and Narayan and Sharma, 2014). The overall conclusion of all of this literature is that for oil-importing countries such as the US, oil prices do have a statistical significant impact on stock prices. Higher oil prices dampen stock prices. For a review of this topic, see Sadorsky (2019).

Turning to banking, Kim (2020) explains the recently lessened impacts of commodity price shocks on the US economy with the increase, since the mid-2000s, in trading in commodity derivatives that are, in turn, included by banks among their assets. He rationalizes his empirical findings by postulating a structural model with financial intermediaries holding commodity derivatives on the asset side of their balance sheets. However, as he points out, the data show that before 2007Q4, the value of financial intermediaries' net long position of commodity derivative contracts was null, while during the 2007Q4 to 2015Q3 period, it was on average 1.1 percent of the remaining total assets. All that suggests that his proposed channel is empirically irrelevant in our sample. This is the reason why we do not incorporate such a channel into our model. Ehouman (2020) emphasizes how the shale oil industry could trigger turmoil in both oil and financial markets in the US. Bidder et al. (2021), although they do not primarily focus on oil price 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, and 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.[6] Wang (2021) conducts a similar analysis, but focusing on regional banks. The last three papers seem to suggest a mechanism that is the complete opposite of the one we propose. In fact, their evidence implies that low oil price is bad news for banks. This apparent contradiction can be easily explained by the fact that these papers all focus on those banks exposed to the oil sector in the US in the period 2014-2016. Actually, that exposure was not large and did not pose any major problem to those banks and to the overall banking sector, as explained in Baumeister and Kilian (2016) and in the Moody's reports cited above. We will return to this point in more detail later on. In this group it is worth mentioning ElFayoumi (2019). Like us, but in a VAR setup, he finds the existence of a balance sheet effect of the oil price. However, that is not related to banks', but rather to firms' balance sheets. He uses US industry level data to find that the impact of structural oil market shocks on the balance sheets of US firms depends on the structural driver causing the change in oil prices and the industrial activity. He does not study how oil price shocks transmit to the rest of the economy.

Finally, our paper is related to those contributions analyzing different aspects of oil price fluctuations through the lens of a DSGE model for the US economy. The earlier studies on this topic mainly adopted real business cycle (RBC) models. Kim and Loungani (1992) include energy as a third input in the production function to improve the explicative power of the model in terms of the US business cycle. Rotemberg and Woodford (1996) use a model with imperfect competition. In their model mark-up pricing amplifies the effect of an oil price increase. Finn (2000) considers a model of the US economy in which energy costs affect output not only directly but also indirectly. In her setup energy prices influence capacity utilization. Leduc and Sill (2004) investigate the response of US monetary policy to oil price shocks by using a calibrated general equilibrium model in which oil use is tied to capital utilization. Carlstrom and Fuerst (2006) include the price of oil in a new Keynesian setup.

Bodenstein et al. (2008) and Nakov and Pescatori (2010) develop DSGE models to study

[6] Bidder et al. (2021) also show that the effect on total lending, total size of the balance sheet, and the degree of leverage appears to be ambiguous.

the relationship between oil price fluctuations and monetary policy. Bodenstein et al. (2011) and Bodenstein et al. (2012) assume an endogenous determination of the real oil price in a new Keynesian framework. Bodenstein et al. (2013) have studied the effects of oil price shocks when the nominal interest rate reaches the zero lower bound (ZLB). More recently, Balke and Brown (2018) consider a medium-size DSGE model to estimate the elasticity of GDP with respect to an oil price shock. In the previous section, we mentioned the paper by Bjornland et al. (2018) in which they use a DSGE model to analyze the role of oil price volatility in reducing US macroeconomic instability and revisit the timing of the Great Moderation and the sources of changes in the volatility of macroeconomic variables. From a theoretical point of view, our paper presents one major difference with respect to all of those papers: those models do not include financial frictions of any sort.

2 Baseline Model

In this section, we describe our DSGE model which embeds financial frictions in line with the paper of Gertler and Karadi (2011) in a real business cycle context.[7] As in Bjornland et al. (2018), we assume the oil production occurs in an individual sector located outside the US. Oil is introduced into the model through the production function of final-goods-producing firms.

2.1 Households

Members of each representative household are divided into workers and bankers. Workers supply labor and receive wages that return to the representative household. Bankers manage financial intermediaries, and they also return their earnings to the representative household. This implies that the representative household actually owns the financial intermediaries that its bankers manage. However, the deposits in financial intermediaries are not owned by the representative household. As in Gertler and Karadi (2011), we assume that there is

[7] Bodenstein and Guerrieri (2012) find that nominal rigidities and monetary policy are not important transmission channels for shocks that affect oil prices.

perfect consumption insurance in each representative household.

We assume that the fraction of workers in the representative household corresponds to $1-d$, whereas the fraction of bankers is d. Over time, individuals can switch from workers to bankers and vice-versa. More specifically, the probability that a banker in the current period remains a banker in the next period is given by θ_t, which we also label a net worth shock. Such a probability does not depend on how long the individual has been a banker. Accordingly, we have that the average survival time for a banker in any given period is $1/(1-\theta_t)$. This implies that every period $(1-\theta_t)d$ bankers switch to workers. The same number of workers randomly switches to bankers. Thus, the two fractions remain fixed at any time. Moreover, we assume that the retained earnings of the bankers that exit are given to the respective household. Also, the representative household provides its new bankers with some start-up funds.

The representative household maximizes the following utility function with respect to consumption, C_t, and labor, L_t:

$$\begin{aligned} &\max E_t \sum_{i=0}^{\infty} \beta^i \left[\ln \left(C_{t+i} - hC_{t+i-1} \right) - \frac{\chi}{1+\varphi} L_{t+i}^{1+\varphi} \right] \\ &\text{where} : 0 < \beta < 1,\ 0 < h < 1,\ \varphi > 0 \end{aligned} \tag{1}$$

In equation (1), β corresponds to the discount rate, χ the relative utility weight of labor, φ the inverse Frisch elasticity of labor supply and h the habit consumption parameter.

The representative household faces the following budget constraint:

$$C_t = W_t L_t + \Pi_t + T_t + R_t B_t - B_{t+1} \tag{2}$$

In equation (2), W_t denotes the real wage, Π_t the net payouts to the household from ownership of both non-financial and financial firms, T_t the lump-sum taxes, B_{t+1} the total quantity of short-term debt the household acquires and R_t the gross real interest rate.

The firs- order conditions for labor supply and consumption are:

$$\begin{aligned} &\Psi_t W_t = \chi L_t^{\varphi} \\ &\text{with} : \Psi_t = \left(C_t - hC_{t-1} \right)^{-1} - \beta h E_t \left[\left(C_{t+1} - hC_t \right)^{-1} \right] \end{aligned} \tag{3}$$

and:

$$E_t \beta \Lambda_{t,t+1} R_{t+1} = 1 \tag{4}$$
$$\text{with} : \Lambda_{t,t+1} \equiv \frac{\Psi_{t+1}}{\Psi_t}$$

where Ψ_t is the marginal utility of consumption and Λ_t the stochastic discount rate.

2.2 Financial Intermediaries

Financial intermediaries lend funds obtained from households to a non-financial final-goods-producing firm. The banker j has the following balance sheet:

$$Q_t S_{j,t} = N_{j,t} + B_{j,t+1} \tag{5}$$

In equation (5), Q_t corresponds to the price of financial assets, $S_{j,t}$ the quantity of financial claims on non-financial firms that the banker holds, $N_{j,t}$ the amount of wealth (net worth) that an intermediary has at the end of period t, and $B_{j,t+1}$ the deposits the banker obtains from households.

The evolution of the intermediary's equity capital is given by:

$$N_{j,t+1} = R_{k,t+1} Q_t S_{j,t} - R_{t+1} B_{j,t+1} \tag{6}$$
$$= \left(R_{k,t+1} - R_{t+1}\right) Q_t S_{j,t} + R_{t+1} N_{j,t} \tag{7}$$

where $R_{k,t}$ is the return on capital.

The banker operates only if the following inequality holds:

$$E_t \beta^j \Lambda_{t,t+1+i} \left(R_{k,t+1+i} - R_{t+1+i}\right) \geq 0, \ i \geq 0 \tag{8}$$

The intermediary's aim is to maximize expected terminal wealth. Formally, this is given by:

$$\begin{aligned} V_{j,t} &= \max E_t \sum_{i=0}^{\infty} \left(1 - \theta_{t+i}\right) \theta_{t+i}^{i} \beta^{i+1} \Lambda_{t,t+1+i} N_{j,t+1+i} \\ &= \max E_t \sum_{i=0}^{\infty} \left(1 - \theta_{t+i}\right) \theta_{t+i}^{i} \beta^{i+1} \left[\begin{array}{c} \Lambda_{t,t+1+i} \left(R_{k,t+1+i} - R_{t+1+i}\right) \cdot \\ Q_{t+i} S_{j,t+i} + R_{t+1+i} N_{j,t+1+i} \end{array} \right] \end{aligned} \tag{9}$$

The banker has the incentive to borrow additional funds from the representative household and expand its assets indefinitely, as long as equation (8) holds. To impose a limit on that, we introduce the following moral hazard/costly enforcement (or agency) problem. At the beginning of each period, the intermediary has the option of moving the time-varying fraction λ_t from the project to its representative household.[8] We label this a divert shock. This creates the right incentives because the cost to the banker is that depositors can force the intermediary into bankruptcy and recover the remaining fraction $1 - \lambda_t$ of assets, but it is too costly for the depositors to recover the fraction λ_t.

Accordingly, lenders supply funds to the intermediary only if the following incentive constraint is satisfied:

$$V_{j,t} \geq \lambda_t Q_t S_{j,t} \tag{10}$$

that is, the loss by diverting a fraction of assets is greater than the gain from doing so. In fact, the left-hand side represents the wealth a banker would lose if forced into bankruptcy, while the right-hand side is the amount of assets the bankrupt banker can retain because depositors cannot afford to recover them.

Moreover, $V_{j,t}$ can be expressed as follows:

$$V_{j,t} = \upsilon_t Q_t S_{j,t} + \eta_t N_{j,t} \tag{11}$$

In the previous expression, we have that:

$$\upsilon_t = E_t \left\{ (1 - \theta_t) \beta \Lambda_{t,t+1} \left(R_{k,t+1} - R_{t+1} \right) + \beta \Lambda_{t,t+1} \theta_{t+1} X_{t,t+1} \upsilon_{t+1} \right\} \tag{12}$$

and:

$$\eta_t = E_t \left\{ (1 - \theta_t) + \beta \Lambda_{t,t+1} \theta_{t+1} F_{t,t+1} \eta_{t+1} \right\} \tag{13}$$

In equations (12) and (13), υ_t can be interpreted as the expected discounted marginal gain to the banker of expanding assets $Q_t S_{j,t}$ by a unit, holding net worth $N_{j,t}$ constant, $X_{t,t+i} \equiv$

[8] Other papers that make a similar assumption about the time-varying nature of this parameter are Sims and Wu (2021), Gelain and Ilbas (2017-May), Dedola et al. (2013), and Bean et al. (2010).

$Q_{t+i}S_{j,t+i}/Q_tS_{j,t}$, η_t as the expected discounted value of having another unit of $N_{j,t}$, holding $S_{j,t}$ constant, and $F_{t,t+i} \equiv N_{j,t+i}/N_{j,t}$.

The incentive constraint can be rewritten as:

$$\eta_t N_{j,t} + \upsilon_t Q_t S_{j,t} \geq \lambda_t Q_t S_{j,t} \tag{14}$$

Given this constraint, and assuming that it is binding, the equity capital of the intermediary determines the assets she can buy:

$$Q_t S_{j,t} = \frac{\eta_t}{\lambda_t - \upsilon_t} N_{j,t} = \phi_t N_{j,t} \tag{15}$$

In equation (15), ϕ_t represents the private leverage ratio, that is, the ratio of privately intermediated assets to equity. The constraint (15) limits the intermediaries' leverage ratio to the point where the banker's incentive to cheat is exactly balanced by the cost. In this respect the agency problem leads to an endogenous capital constraint on the intermediary's ability to acquire assets.

Over time, the net worth of the intermediary evolves according to:

$$N_{j,t+1} = \left[\left(R_{k,t+1} - R_{t+1}\right)\phi_t + R_{t+1}\right] N_{j,t} \tag{16}$$

Moreover, we have that:

$$F_{t,t+1} = \frac{N_{j,t+1}}{N_{j,t}} = \left(R_{k,t+1} - R_{t+1}\right)\phi_t + R_{t+1} \tag{17}$$

and:

$$X_{t,t+1} = \frac{Q_{t+1}S_{j,t+2}}{Q_t S_{j,t+1}} = \left(\frac{\phi_{t+1}}{\phi_t}\right)\left(\frac{N_{j,t+1}}{N_{j,t}}\right) = \left(\frac{\phi_{t+1}}{\phi_t}\right) F_{t,t+1} \tag{18}$$

In order to determine the banker's total demand for assets we sum across individual demands. Therefore, we have that:

$$Q_t S_t = \phi_t N_t \tag{19}$$

where S_t denotes the aggregate quantity of the banker's assets and N_t indicates the aggregate intermediary capital.

We assume that the banker's aggregate capital is given by the sum of the net worth of existing bankers, $N_{e,t}$, and the net worth of entering bankers, $N_{n,t}$:

$$N_t = N_{e,t} + N_{n,t} \tag{20}$$

We know that the fraction θ_t of intermediaries at $t-1$ survives until t. This implies $N_{e,t}$ evolves according to:

$$N_{e,t} = \theta_t \left[\left(R_{k,t} - R_t \right) \phi_{t-1} + R_t \right] N_{t-1} \tag{21}$$

The total final period assets of exiting intermediaries at t is $(1-\theta_t)\, Q_t S_{t-1}$. We also assume that each period, the household transfers a fraction $\frac{\omega}{1-\theta_t}$ of this value to its entering bankers. In aggregate terms we have that:

$$N_{n,t} = \omega Q_t S_{t-1} \tag{22}$$

In equation (22), ω is the proportional transfer to the entering intermediaries.

Finally, we combine equations (21) and (22) in order to get an equation of motion for N_t:

$$N_t = \theta_t \left[\left(R_{k,t} - R_t \right) \phi_{t-1} + R_t \right] N_{t-1} + \omega Q_t S_{t-1} \tag{23}$$

2.3 Final-Goods-Producing Firms

Firms that produce final goods work in a perfectly competitive environment.[9] As in Gertler and Karadi (2011), we assume that at the end of period t, the firm buys capital K_{t+1} that it uses in the following period. After production takes place, in period $t+1$, the firm can sell the capital in the open market.

In order to acquire capital, the firm uses funds from the bankers. The firm issues S_t claims equal to the number of units of capital that it bought, K_{t+1}. The price of each claim is exactly equal to the price of a unit of capital, Q_t. Accordingly, the value of capital

[9] In Gertler and Karadi (2011) this segment of the production process occurs with intermediate goods producers. Final output is a CES composite of a continuum of mass unity of differentiated retail firms that use intermediate output as the sole input. They simply re-package intermediate output. They operate in a monopolistic competitive environment, so they can charge a mark-up over their marginal costs. They are also subject to frictions in setting their price, so they determine the evolution of price inflation. We work with a real business cycle model, so we do not need to make the distinction between intermediate and final goods producers. In our case marginal costs are constant and equal to 1.

acquired is given by $Q_t K_{t+1}$, whereas the value of claims is given by $Q_t S_t$. Thus, the arbitrage condition is given by:

$$Q_t K_{t+1} = Q_t S_t \tag{24}$$

As in Gertler and Karadi (2011), we assume that there are no frictions in the process of non-financial final-goods-producing firms obtaining funding from intermediaries. The intermediary has perfect information about the firm and has no problem enforcing payoffs. This contrasts with the process of the intermediary obtaining funding from households. Thus, within the model, only intermediaries face capital constraints on obtaining funds. These constraints, however, affect the supply of funds available to non-financial final-goods-producing firms and hence the required rate of return on capital these firms must pay. Conditional on this required return, however, the financing process is frictionless for non-financial final-goods-producing firms. The firm is thus able to offer the intermediary a perfectly state-contingent security, which is best thought of as equity (or perfectly state-contingent debt).

Following Kim and Loungani (1992), Backus and Crucini (2000) and Lippi and Nobili (2012), final goods are produced using capital (K_t), labor (L_t), and oil ($O_{y,t}$), and capital and oil are nested as a CES function within a Cobb-Douglas production function:

$$Y_t = (Z_t L_t)^{\alpha} \left[\omega_k \left(U_t \xi_t K_t\right)^{1-\varrho} + (1-\omega_k) O_{y,t}^{1-\varrho}\right]^{\frac{1-\alpha}{1-\varrho}} \tag{25}$$

In equation (25), the share of labor input is denoted by α, the oil weight in technology corresponds to $1-\omega_k$, whereas ϱ determines the elasticity of substitution between oil and capital. Moreover, Z_t represents exogenous labor-augmenting technological progress or, equivalently, a neutral technology factor. The level of neutral technology is non-stationary and its growth rate ($z_t \equiv \Delta ln Z_t$) follows an AR(1) process:

$$z_t = (1-\rho_z)\gamma + \rho_z z_{t-1} + \sigma_z \varepsilon_t^z \tag{26}$$

In equation (25), U_t is the capital utilization and ξ_t the quality of capital shock (so that $\xi_t K_t$ is the effective quantity of capital at time t). The shock ξ_t is meant to provide a simple source of exogenous variation in the value of capital.[10] We assume that the depreciation rate is given by:

$$\delta\left(U_t\right) = \delta_c + \frac{b}{1+\zeta} U_t^{1+\zeta} \tag{27}$$

At time t, the firm chooses the utilization rate, the labor demand, and the oil demand (given the real price of oil $P_{o,t}$) as follows:

$$\left(1-\alpha\right)\omega_k \frac{Y_t}{U_t^{\varrho}} \left(\frac{\xi_t K_t}{A_t}\right)^{1-\varrho} = bU_t^{\zeta} \xi_t K_t \tag{28}$$

$$W_t = \alpha \frac{Y_t}{L_t} \tag{29}$$

$$P_{o,t} = \left(1-\alpha\right)\left(1-\omega_k\right) \frac{Y_t}{O_{y,t}^{\varrho}} \frac{1}{\left(A_t\right)^{1-\varrho}} \tag{30}$$

where:

$$A_t = \left[\omega_k \left(U_t \xi_t K_t\right)^{1-\varrho} + \left(1-\omega_k\right) O_{y,t}^{1-\varrho}\right]^{\frac{1}{1-\varrho}}$$

Given that the firm earns zero profits state by state, because there are no adjustment costs and thus the firms' capital choice problem is always static, it simply pays out the ex post return to capital to the intermediary. Accordingly R_{t+1}^k is given by:

$$R_{t+1}^k = \frac{\xi_{t+1}\left[\ \left(1-\alpha\right)\omega_k \frac{Y_{t+1}}{\xi_{t+1} K_{t+1}^{\varrho}} \left(\frac{U_{t+1}\xi_{t+1}}{A_{t+1}}\right)^{1-\varrho} + Q_{t+1} - \delta\left(U_{t+1}\right)\ \right]}{Q_t} \tag{31}$$

It is easy to see that if $\omega_k = 1$ and $\varrho = 0$, the production function boils down to a Cobb-Douglas function and equations (28), (29), and (31) are the same as in Gertler and Karadi (2011).

[10] Gourio (2012) elaborates as follows on the quality of capital shock: "Capital destruction is clearly realistic for wars or natural disasters, but obviously not for economic depressions. The assumption requires in this case a broader interpretation as a shock to the quality of capital. Perhaps it is not the physical capital but the intangible capital (customer and employee value) that is destroyed during prolonged economic depressions. Moreover, economic crises often lead to microeconomic volatility and large reallocation, implying that some specialized capital goods may become worthless. Finally, expropriation of capital may be equivalent to capital destruction, if the capital is taken away and not used as effectively".

2.4 Capital-Producing Firms

Capital-producing firms are perfectly competitive. At the end of period t, they buy capital from final-goods-producing firms. Then, they repair the depreciated capital and build new capital. In turn, they sell both the new and the repaired capital. The worn-out capital can be replaced at a cost of unity. We denote by Q_t the value of a new unit of capital. Following Gertler and Karadi (2011), we assume that there are no adjustment costs associated with refurbishing capital, whereas there are adjustment costs in the production of new capital. Since the households own the capital-producing firms, they receive their profits. Net investment is given by:

$$I_{n,t} = I_t - \delta\left(U_t\right)\xi_t K_t \tag{32}$$

where I_t is gross investment.

The capital accumulation equation is given by:

$$K_{t+1} = \xi_t K_t + I_{n,t} \tag{33}$$

Therefore, we can write the discounted profits for a capital producer as:

$$\begin{aligned} &\max E_t \sum_{\tau=t}^{\infty} \beta^{T-t} \Lambda_{t,\tau} \left\{ \left(Q_\tau - 1\right) I_{n,\tau} - f\left(\tfrac{I_{n\tau}+I}{I_{n\tau-1}+I}\right)\left(I_{n,\tau}+I\right) \right\} \\ &\text{with} : I_{n,t} = I_t - \delta\left(U_t\right)\xi_t K_t \end{aligned} \tag{34}$$

where $f(1) = f^{'}(1) = 0$ and $f^{''}(1) > 0$, and where $\delta\left(U_t\right)\xi_t K_t$ is the quantity of capital refurbished.

The first-order condition for net investment is given by:

$$Q_t = 1 + f(\cdot) + \left(\frac{I_{n,t}+I}{I_{n,t-1}+I}\right) f^{'}(\cdot) - E_t \beta \Lambda_{t,t+1} \left(\frac{I_{n,t+1}+I}{I_{n,t}+I}\right)^2 f^{'}(\cdot) \tag{35}$$

2.5 Oil Sector

We model the oil sector following Bjornland et al. (2018).[11] As they do, we assume that the price of oil is determined by a single sector located outside the US. This sector is modeled

[11] Differently from them, we do not consider the time-varying dimension and the multiplicity of regimes among which the economy can switch.

as a bi-variate structural VAR (SVAR) as follows:

$$A_0 \begin{bmatrix} \Delta \ln(GDP_t^W) \\ \ln(P_{o,t}) \end{bmatrix} = c + \sum_{j=1}^{p} A_j \begin{bmatrix} \Delta \ln(GDP_{t-j}^W) \\ \ln(P_{o,t-j}) \end{bmatrix} + \begin{bmatrix} \varepsilon_t^W \\ \varepsilon_t^{P_o} \end{bmatrix} \tag{36}$$

where $\Delta \ln(GDP_t^W)$ denotes the growth rate of world GDP, and $P_{o,t}$ is the real oil price. The two ε_t^W and $\varepsilon_t^{P_o}$ are independently and identically distributed $N(0, \Omega_\varepsilon)$, with $\Omega_\varepsilon = E(\varepsilon_t \varepsilon_t')$, and $\varepsilon_t = [\varepsilon_t^W, \varepsilon_t^{P_o}]'$. Moreover, A_0 is a lower triangular matrix, implying a lagged response of activity to an innovation to the price of oil, whereas oil prices can respond contemporaneously to an innovation to world demand. The number of lags is 2.

The previous literature has devoted a lot of attention to the identification of oil market shocks through SVAR models. In the robustness tests in Section (5), we consider several alternatives to the SVAR model of equation (36) to account for a number of issues raised in Kilian (forthcoming), Kilian and Zhou (forthcoming), and Kilian (2022a). We show that our results remain unchanged to all those alternatives.

2.6 Resource Constraint and Government Policy

The aggregate resource constraint of the economy is given by:

$$Y_t = P_{o,t} O_{y,t} + C_t + I_t + G_t + f\left(\frac{I_{n,t} + I}{I_{n,t-1} + I}\right)(I_{n,t} + I) \tag{37}$$

where output is divided between consumption, investment, and government consumption, G_t.

The government budget constraint is given by:

$$G_t = T_t \tag{38}$$

where government expenditure is financed by lump-sum taxes.

2.7 Exogenous Shocks

In addition to the stationary technology shock already described, the other shocks in the model follow AR(1) processes. They are the quality of capital shock, the government spending shock, the net worth shock, and the divert shock. They all vary exogenously over time in response to independently and identically distributed $N(0,1)$ innovations ε_t^i, $i = \xi, g, \theta, \lambda$, as follows:

$$\ln(\xi_t) = (1-\rho_\xi)\ln\xi + \rho_\xi \ln(\xi_{t-1}) + \sigma_\xi \varepsilon_t^\xi \tag{39}$$

$$\ln(G_t) = (1-\rho_g)\ln g + \rho_g \ln(G_{t-1}) + \sigma_g \varepsilon_t^g \tag{40}$$

$$\ln(\theta_t) = (1-\rho_\theta)\ln\theta + \rho_\theta \ln(\theta_{t-1}) + \sigma_\theta \varepsilon_t^\theta \tag{41}$$

$$\ln(\lambda_t) = (1-\rho_\lambda)\ln\lambda + \rho_\lambda \ln(\lambda_{t-1}) + \sigma_\lambda \varepsilon_t^\lambda \tag{42}$$

3 Estimation

In this section, we discuss the data we use to estimate our model and we provide some details of the estimation procedure. Then, we describe how we calibrate some of the model parameters and how we estimate the remainder.

3.1 Data

Our model is estimated using Bayesian methods for the sample period 1992Q1-2019Q4. We use the following observed variables: real per capita GDP growth, real per capita consumption growth, real per capita investment growth, the spread between the BAA corporate bond yield and the 10-year government bond yield, the Dow Jones US bank stock market index growth, the growth rate of world GDP, and the real price of oil.[12] A detailed description of the data and their transformation is in Appendix A. We plot them in Figure 1. The measurement equations for those variables not pertaining to the oil sector are as follows:

$$\begin{aligned}
\text{Output growth} &= \ln(y_t) - \ln(y_{t-1}) + z_t \\
\text{Consumption growth} &= \ln(c_t) - \ln(c_{t-1}) + z_t \\
\text{Investment growth} &= \ln(i_t) - \ln(i_{t-1}) + z_t \\
\text{Net worth growth} &= \ln(n_t) - \ln(n_{t-1}) + z_t \\
\text{Spread} &= E_t[\ln\left(R_{t+1}^k\right) - \ln(R_{t+1})]
\end{aligned}$$

[12]The choice of financial variables is in line with Christiano et al. (2014).

where lower-case letters correspond to stationary variables as defined in Appendix B.

The Bayesian estimation is performed by setting prior distributions for the parameters and by estimating the posterior distributions by maximizing the log-posterior function, which combines the prior information on the parameters with the likelihood of the data. The Metropolis-Hastings algorithm is used to obtain a complete picture of the posterior distribution. We run two Metropolis-Hastings chains of 400,000 iterations each, with a 20 percent burn-in. Brooks and Gelman's (1998) multivariate convergence statistics of MCMC are presented in Appendix D together with the full posterior distributions.

3.2 Calibrated Parameters and Prior Distributions

Preferences. We calibrate β at 0.9959. The inverse Frisch elasticity of labor supply, φ, is calibrated at 0.2760, the value in Gertler and Karadi (2011).

Production. The elasticity of marginal depreciation with respect to the utilization rate, ζ, is calibrated at 7.2 following the estimated value by Primiceri et al. (2006). The share of labor in the production function, α, is equal to 0.64, as in Lippi and Nobili (2012). The depreciation rate of capital, $\delta(U)$, corresponds to an annual capital depreciation of 10 percent. Following Lippi and Nobili (2012), we assume that the oil weight in the production function, $1-\omega_k$, corresponds to 0.10. Based on data from the Energy Information Administration of the US Department of Energy, we set the overall oil share of the domestic economy to 3.9 percent of GDP. The value of the elasticity of substitution between capital and oil in the production function, $1/\varrho$, is computed from steady state restrictions to match the overall share of oil in GDP. Such a value corresponds to 0.9836, calculated by assigning the posterior mode values to the estimated parameters. The quarterly trend growth rate of GDP, γ, is computed as the average growth rate of the real per capita GDP over our sample period and it is equal to 1.0035. We calibrate the government spending to output ratio at 0.2.

Financial Intermediaries. We calibrate the steady state value of the gross external finance premium, R^k/R, based on the quarterly average of the observed gross premium in the sample, i.e., 1.0060. Moreover, we set the leverage ratio steady state value, ϕ, and the proportional transfer to entering bankers, ω, equal to those assumed by Gertler and Karadi (2011), i.e., 4 and 0.0022, respectively. The divert fraction λ is implied by steady state restrictions. It turns out to be 0.71, calculated by assigning the posterior mode values to the estimated parameters. This is higher than the value in Gertler and Karadi (2011), i.e., 0.38, but it is the same as in Gelain and Ilbas (2017-May). The latter authors explain that this depends on the calibrated steady state value of the finance premium, double compared to Gertler and Karadi's (2011) calibration.[13] We re-estimate our model with a premium steady state value of 1 percent (1.0025 in gross quarterly terms) and the implied value of λ becomes 0.44. This does not affect our results. The only implication is a small reshuffling between the importance of the technology shock versus the quality of capital shock.

The bottom part of Table 1 presents the values of the parameters implied by steady state restrictions, as reported in Appendix C. Since they can differ slightly across model specifications, we show them for the four models we analyze.

Priors of Estimated Parameters. Table 2 reports the priors of the parameters that are estimated with Bayesian techniques. The prior distribution for habit in consumption, h, is agnostic. Therefore, it is a Beta distribution with mean 0.5 and standard deviation 0.2. The prior mean for the investment adjustment cost parameter, η_i, receives a very shared prior distribution in the literature.[14] We follow that and we set a Gamma distribution with mean 4 and standard deviation 1.

Turning to the priors of the exogenous shocks of our model, we set the persistence parameters for all AR(1) processes to be Beta distributions with means of 0.50 and standard deviations of 0.20. We use Inverse Gamma distributions for the standard deviations of all the innovations of the exogenous shocks with means equal to 0.1 and standard deviations of 3.

[13] To motivate their net 1 percent steady state premium in annual terms, Gertler and Karadi (2011) state: "We base the steady state target for the spread on the pre-2007 spreads between mortgage rates and government bonds and between BAA corporate versus government bonds". In the period 1992Q1-2006Q4, the former has an average of 1.60 percent, while the latter has an average of 2.09. Our calibration is more in line with our sample data.

[14] See, for instance, Smets and Wouters (2007) or Justiniano et al. (2013).

As for the prior distributions of the VAR parameters we estimate the reduced-form parameters. We define:

$$m_t = \left[\Delta \ln(GDP_t^W), \ln(P_{o,t})\right]'$$

$$\varepsilon_t = \left[\varepsilon_t^W, \varepsilon_t^{P_o}\right]'$$

The system of equations of the oil sector in (36) can then be written as:

$$A_0 m_t = A_1 m_{t-1} + \varepsilon_t$$

$$m_t = A_0^{-1} A_1 m_{t-1} + A_0^{-1} \varepsilon_t$$

$$m_t = B m_{t-1} + u_t$$

where B is the 4×2 matrix of the VAR coefficients on lagged variables, and u_t is independently and identically distributed $N(0, \Sigma_u)$. The variance-covariance matrix of u_t is given by:

$$\Sigma_u = \begin{bmatrix} \sigma_W^2 & cov\left(u_t^W, u_t^{P_o}\right) \\ cov\left(u_t^{P_o}, u_t^W\right) & \sigma_{P_o}^2 \end{bmatrix}$$

We estimate the parameters in the B matrix, the standard deviations σ_W, σ_{P_o}, and the correlation $corr(u_t^W, u_t^{P_o})$, together with the other parameters of our DSGE model.[15] To get a sense of how to set their prior distribution moments, we first estimate the VAR separately with OLS. We then assume Normal prior distributions for all those parameters centered at the OLS estimates.

4 Results

In this section we present our results. We start by assessing oil sector dynamics as described in the SVAR model. We continue by describing our model dynamics when an oil price shock hits the economy. Then, we present the real per capita GDP growth variance decomposition

[15]The correlation between the two residuals is defined as:

$$corr\left(u_t^W, u_t^{P_o}\right) = \frac{cov\left(u_t^W, u_t^{P_o}\right)}{\sigma_W \sigma_{P_o}}$$

to determine the relative importance of different shocks in explaining its variability, and the real per capita GDP growth historical shock decomposition to zoom-in on some specific events. We conclude with a counterfactual analysis to establish the role of oil price shocks in determining the size of the real per capita GDP growth that would prevail in a world without oil price shocks.

4.1 Oil Sector SVAR Dynamics

We present the SVAR dynamics in Figure 2. A positive innovation to the growth rate of world GDP generates a very persistent and highly significant increase in that variable. This shock also boosts the real price of oil. A positive innovation to the real price of oil generates an immediate, large, and persistent positive effect on that variable and a temporary increase in world GDP, followed by a drop. Not surprisingly, our oil sector narrative is in line with that of Bjornland et al. (2018).

4.2 Oil Price Shock Dynamics

In Figure 3 we report the response of a set of endogenous variables to an estimated one standard deviation shock to the price of oil. We focus primarily on this shock because we find that it is the most relevant in explaining oil price fluctuations. We consider two versions of the estimated model: a real business cycle model with oil only (solid blue lines) and our baseline model with banking and oil (dashed red lines).[16] We report the 5th and the 95th percentiles of the Bayesian impulse response functions to evaluate them statistically.

The shock is basically the same for both models, because there is no feedback from the DSGE to the SVAR. Starting with the no-banking model, an increase in the price of makes oil more expensive. Firms reduce their demand for oil. With less input, they cut production. As a result, they invest less and decrease their demand for capital. The price of capital (or assets' value) drops as a consequence. The no-banking model dynamics end with

[16] Alternatively, we could have considered the solid blue line case as the outcome of shutting off the accelerator channel in our baseline model. We would have obtained the same results.

that.[17] As for the baseline model, there are further implications. In fact, the drop in asset prices generated by the negative oil price shock triggers a deterioration of the intermediaries' balance sheet in our baseline model and, because of the leverage constraint as in equation (19), a decrease in their net worth.[18] Associated with the drop in intermediaries' capital, given the resulting disruption in borrowing and lending activity, there is a sharp increase in the credit spread.[19] Firms face a higher cost of borrowing and they have to reduce their demand for capital and investments, magnifying the initial negative input-cost effect of the increased price of oil. That second-round effect transmits also to production (and to asset prices).

We have described the conventional financial accelerator effect embedded in Gertler and Karadi (2011). As one can appreciate from Figure 3, it is statistically significant for all variables, since all of the impulse response functions do not overlap, meaning that they are statistically different from each other. We can conclude that the banks' balance-sheet channel enhances the direct effects of oil price shocks on the US economy.

How do our model dynamics relate to the literature? There are no references for our baseline model, since we are the first to estimate the effect of oil price shocks on GDP (and other variables) when the financial accelerator is explicitly taken into account. However, it is worth comparing our model *without* banking to previous works. Two papers in particular are more directly comparable with ours. The first is Bjornland et al. (2018). They find that following an oil price shock that increases the price of oil by 10 percent, US GDP declines by 0.15 percent after 4 quarters. By re-scaling our impulse response functions to that shock size, we find that GDP declines by 0.53 percent after 4 quarters, calculated by assigning the posterior mode values to the estimated parameters. The other paper is Lippi

[17]We share this exact operating mechanism with Bjornland et al. (2018).

[18]The decrease oin stock market measures following an oil price shock is consistent with the empirical evidence in Kilian and Park (2009) and Aastveit (2014). Moreover, the effect of oil price shocks on banks' assets is consistent with the analysis in Moody (2015c): "lower energy costs will help boost US GDP. Increased business investment and real wages will support the debt-repayment capacity of borrowers and the *overall asset quality* of US banks".

[19]The increase of the credit spread following an oil price shock is consistent with the empirical evidence in Abbritti et al. (2020).

and Nobili (2012), from which we borrow the production function specification and some of its parameters' calibration. They find that both a rest of the world demand shock and an oil-specific demand shock that increase the price of oil by 10 percent reduce US GDP by 1 percent after 4 quarters. Hence our model positions itself in between those two references, but is closer to Bjornland et al. (2018). Empirical evidence based on papers without DSGE models, such as Aastveit et al. (2015), finds the effect on GDP under the same circumstances to be around 0.20 percent, although this is an average across the developed countries in their analysis.[20] Despite being a bit on the high side, the relatively large response of GDP to the oil price shock in our model without banking sector does not allow to that shock to play an important role in explaining the real economy fluctuations, as we will show in the next sections.

On the contrary, our baseline model, with both oil and banking, suggests a response of GDP of 0.71 percent after 4 quarters from the moment a 10 percent oil price shock has occurred, calculated by assigning the posterior mode values to the estimated parameters. Hence, neglecting financial factors seems to imply an underestimation of the effects of the oil price shocks on GDP.

4.3 Variance Decomposition

In Table 3 we report the GDP growth variance decomposition for different horizons and for four specifications of our model to grab the contribution of the single elements we consider. We analyze a real business cycle model (first column), to which we add the oil sector (second column), a banking sector only model (third column), and our baseline model (fourth

[20]Another set of papers give a sense of the magnitude of the effect of exogenous movements in the price of oil on GDP, despite the fact that they mostly focus on oil supply shocks. Hamilton (2003) finds, for the period 1949-1980, that a 10 percent increase in oil prices will result 4 quarters later in a level of GDP that is 1.4 percent lower than it otherwise would be. The effect reduces to 0.26 percent if the sample considered is 1949-2001. The evidence in Hamilton (2003) and Hamilton and Herrera (2004) suggests that the effect is in that range of variation depending on the sample and on the model specification. More recently, using a time-varying analysis and accounting for demand and supply shocks, Baumeister and Peersman (2013) show that from the beginning of the 1990s until 2011, the response of GDP after 4 quarters to a 10 percent increase in the price of oil, generated in their case by an oil supply shock, has been constantly at a value that very closely fluctuates around 0.5 percent.

column). The variance decomposition is computed at the posterior modes.

As for the real business cycle model, we obtain the standard result that the business cycle is mainly driven by the technology shock (at all horizons) which explains around 78 percent of GDP growth variability. The remainder is explained by the government spending shock. Nothing is left for the quality of capital shock. The explanation is related to its estimated autoregressive coefficient ρ_ξ, i.e., 0.02. With such a low persistence, that shock does not capture the right comovement between output and investment, the latter being driven by the wrong sign on asset prices. Hence, it cannot be a relevant shock.

Once we include the oil sector, we notice that the oil price shock counts somewhat, i.e., almost 6 percent. This is a negligible contribution. This is easily explained by the fact that the oil share in the US economy is so small, 3.9 percent, that it relegates the oil price shock to be basically irrelevant on average when the input-cost channel is the only one at play. This evidence is largely shared in the literature (e.g., Rebelo, 2005, Hamilton, 2008, and Kilian, 2014).[21] Moreover, our percentage aligns very well with the evidence in Bjornland et al. (2018). Across a set of four different regimes that might well describe the dynamics in our sample, i.e., high and/or low volatility of the macroeconomy and/or the oil price with an always hawkish central bank, they find that on average oil price shocks explain between 3 and 5 percent of GDP growth variability in the short to medium run and in the long run, respectively. Our results also indicate that the technology shock loses importance, partly in favor of the oil price shock, which is in principle a good candidate for replicating the comovement in the observables, and partly in favor of the government spending shock in the long run.[22]

In the third column, we show what happens in a model with banks only. Technology is still the most important shock, but somewhat less than in the model without banking. It now explains around 65 percent on average across horizons. One outstanding result is that the quality of capital shock gains importance, settling as the second most important driver

[21] Kilian (2014) states: "The empirical literature based on linear VAR models concludes that oil price shocks statistically explain only a modest fraction of the variation in US growth rates over time".

[22] This is in line with Kim and Loungani (1992), who find that the inclusion of energy price shocks leads to only a modest reduction in the RBC model's reliance on unobserved technology shocks.

of GDP growth, with its 20 percent or so explanatory power.[23] Its estimated persistence is still very low, i.e. 0.07, but we now use financial observables that discipline the estimation. In particular the stock market index which helps shaping the assets price dynamics. As a result, this shock does generate the right co-movement between investment and output despite its low persistence. The divert shock also counts to some extent, explaining about 10 percent. The government spending shock is way less important because the other demand shocks are now well identified by the data.

Finally, the fourth column shows our baseline model. We highlight that the oil price shock is now more relevant. It indeed becomes the second most important shock after the technology shock. It explains 17 percent of GDP growth variability at the 1-quarter ahead horizon, and it quickly settles at 13 percent as the horizon increases. Either way, this result clearly testifies to the importance of the banking sector in characterizing the quantitative relevance of the oil price shock. Without the banking sector, one would greatly underestimate it. The reason why that happens is the financial accelerator mechanism. As we previously described, the same size oil price shock has a bigger impact on the economy when financial frictions are active.

Our findings are in line with the literature investigating the role of *indirect* channels, which finds that oil price shocks influence economic activities beyond that explained by direct input-cost effects. For instance, accounting for a reallocation across sectors channel in a VAR set-up, Davis and Haltiwanger (2001) find that oil price shocks account for 20–25 percent of the variability in employment growth. Lee and Ni (2002) stress that heightened uncertainty is a major reason why oil price shocks induce recessions. Finn (2000) developed a model with an indirect channel based on the fact that energy is essential for the utilization of capital, such that oil shocks are transmitted through endogenous fluctuations in capital utilization. She shows that her model describes the empirical evidence about how the US value added drops after an oil shock better than a model without that channel.

[23] This is consistent with the evidence in Gourio (2012). He finds that fluctuations in macroeconomic risk, defined as a combination of a productivity shock and a depreciation shock to the capital stock (or capital quality shock), contribute to business cycles.

4.4 Historical Shock Decomposition

The variance decomposition gives an average picture about the different shocks. A quarter-by-quarter dissection of the issue can be done by means of a historical decomposition. We report it in Figure 4. We focus on the real business cycle model with oil only (top panel) and our baseline model (bottom panel).

As expected, the technology shock (blue bars) plays a dominant role in the real business cycle model with oil only. In the baseline model, the technology shock is less dominant in favor of financial shocks, mainly the quality of capital shock, and in favor of a more prominent role for oil price shocks.

Zooming-in on the Great Recession, we need to separate its first part (2007Q4-2008Q3) from its second part (2008Q4-2009Q2). The model with oil only interprets the first part as a mixture of positive and negative technology shocks and negative (but small) oil price shocks (red bars). That reflects the run-up in oil prices during that period. As for the second part, the model attributes the collapse in US economic activity to a large negative technology shock. The government spending shock (white bars) contributes positively. Finally, oil price shocks turn positive for the remainder of the recession when the oil prices dropped significantly. Hence, even the model with no financial frictions identifies a role for oil price shocks in this event, but not a very large one. All of the other shocks are totally irrelevant. This narrative is in line with Bjornland et al. (2018) and Balke and Brown (2018).

Turning to the baseline model, we notice that the quality of capital shock (green bars) is more relevant, especially during the Great Recession. This is important because this is the financial shock that is supposed to capture well the dynamics during that period, as described by Gertler and Karadi (2011), and because it gives a more realistic description of the crisis. It is worth stressing that the technology shock is always positive during the first part of the recession, because now the model can account for the negative effects through other (demand) shocks. The oil price shock follows the same pattern as before, but it is now more important (red bars are bigger), stressing once more that financial frictions are crucial to properly assess it.

The other period largely discussed in the media and in the literature is the one from June 2014 to March 2016, during which the real price of oil declined by 66 percent. Many observers expected this oil price shock to boost the US economy. As shown by Baumeister and Kilian (2016), the expected boost was not realized. In fact, the average US real economic growth has increased only slightly, from 1.8 percent in the period 2012Q1-2014Q2 to 2.2 percent in the period 2014Q3-2016Q1. The reason for that has been a compensating effect of raising private real consumption and non-oil-related business investment and a large reduction in real investment by the oil sector.

In terms of the financial sector, there was concern for those US banks exposed to the (shale) oil sector, but banks' exposure to the oil sector was not so worrisome after all. As discussed in Baumeister and Kilian (2016), banks' stock values initially appreciated amid falling oil prices and remained pretty stable until the beginning of 2016, when they sharply declined. Therefore, there is no evidence that financial fragility negatively impacted the US economy. Our model captures that fact very well. Indeed, in our model a decline in oil prices is good news for banks. The increase in domestic goods production due to lower input costs triggers an improvement in banks' balance sheets and, through the accelerator effect, an even more beneficial effect for the economy. Such a result might seem in sharp contrast with the evidence in Bidder et al. (2021) and Wang (2021). However, their focus is on US banks exposed to the oil sector. While those banks are also part of our stock market index, the amount of loans to the oil sector with respect to their total loans was never bigger than 5 percent in that period.[24] This is the reason why turbulence in the oil sector did not materialize on aggregate, as also stressed by Moody (2015b), Moody (2015c), and Moody (2015a).

[24]The top 10 constituents of the DJGL US banks' stock market index are: JP Morgan Chase & Co, Bank of America Corp, Wells Fargo & Co, Citigroup Inc, PNC Finl Services Group, US Bancorp, Truist Financial Corp, First Republic Bank, SVB Financial Group, and Fifth Third Bancorp. In 2016, the ratios between the outstanding debt to the oil and gas sector and the banks' total loans were as follows: Morgan Stanley 5 percent; Citigroup 3.3 percent; Bank of America 2.4 percent; Wells Fargo 1.9 percent; JP Morgan Chase 1.6 percent; PNC 1.3 percent; and US Bancorp 1.2 percent.

4.5 Counterfactual Analysis

The historical decomposition gives a hint to how shocks explain GDP growth over time. However, to properly quantify the contribution of the oil price shock to the US economy, we run the following counterfactual exercise. We feed the two versions of the model considered in the previous section with all of the respective estimated shocks except the oil price shock. The outcome is shown in Figure 5, where for convenience we focus on the Great Recession. The blue lines represent the observed real per capita GDP growth, while the red lines represent the counterfactual growth in the absence of oil price shocks.[25]

This analysis highlights that the Great Recession's trough would have been more negative than the actual trough without the beneficial effect of the drop in the oil price in 2008Q4. In particular in our baseline model, the trough would have been 2.48 percentage points more negative. In a model without banking it would have been only 1.30 percentage points more negative. The first part of the Great Recession instead, i.e., 2007Q4-2008Q3, is characterized by a negative contribution of oil price shocks because the oil price was increasing in those quarters. Therefore, once we eliminate those shocks, GDP growth is much less negative, and is even positive for the most part.

Our narrative of the first part of the Great Recession in terms of the oil price shock, despite being based on different arguments, is consistent with the view in Hamilton (2009). He argues that this episode should be added to the list of US recessions to which oil prices appear to have made a material contribution. In fact, he claims that the run-up in oil prices in that period had a significant negative effect on consumption and, absent that decline, it is unlikely that the period 2007Q4-2008Q3 would have been characterized as one of recession for the United States. We largely confirm Hamilton's analysis about the first part of the Great Recession. But we qualify that the recession after 2008Q3 would have been worse if oil prices had not decreased.

[25] This way of computing the counterfactual is equivalent to eliminating the red bars in Figure 4 and constructing the counterfactual series as the sum of the remaining bars.

5 Robustness

In this section, we run a series of robustness tests and we prove that all of our results are robust. They are related to the sample size, the stationarity of the oil price series, the observables used as proxies for world real economic activity, the frequency of the data used, and the specification of the oil sector SVAR.

Sample Size. Most of the empirical literature considers data from the 1970s. Therefore, we extend our analysis to the period 1974-2019Q4. We do not have data for the DJGL US banks' stock market index prior to 1992; hence, we impute missing observations and we use the Kalman filter to infer them. We still prefer the shorter sample because the DJGL US banks' stock market index is an important variable in our analysis and we want to consider a period for which data are available.

Oil Price Stationarity. Not much attention has been paid to the stationarity of the oil price series in the literature.[26] However, in our sample, that series is not stationary, at least according to a standard stationarity test. To be sure that our results are not driven or affected by that, we estimate our model on two sub-samples, 1992Q1-2004Q4 and 2005Q1-2019Q4, during which oil prices are stationary.

Observables. We followed Bjornland et al. (2018) in using world GDP as a measure of world economic activity. We test two alternative measures: the Kilian index as in Kilian (2009), and the GECON index developed in Baumeister et al. (2022).

Frequency. Kilian (2009) stresses that the Cholesky identification is more appropriate with monthly data. We use quarterly data instead. Hence, we estimate our baseline model at a monthly frequency with mixed-frequency, monthly-quarterly data.

SVAR Specification. We add global crude oil production to the estimation of the oil market SVAR as the first observable, following Kilian (2009). This allows us to highlight two important aspects. First, with the 3x3 specification, one can easily see from Figure E7 that the innovation of the first equation is an oil supply shock, and the other two are

[26] A few examples of studies about oil price stationarity are Maslyuk and Smyth (2008), Sun and Shi (2015), Zaklan et al. (2016), and Landajo et al. (2021).

demand shocks, and they can be labeled as in Kilian (2009). In particular, the last one is an oil-specific demand shock. In Figure E8, we show that the two estimated demand shocks are identical to the two estimated shocks in the 2x2 specification. Second, with regard to the identification of oil price shocks through SVAR models, recent contributions such as Baumeister and Peersman (2013), Baumeister and Hamilton (2019), and Caldara et al. (2019), among others, have found oil supply shocks to be more relevant in explaining oil price fluctuations than our analysis would suggest.[27] In fact, in our specification they are irrelevant. However, as Figure E9 shows, even oil supply shocks generate a statistically relevant financial accelerator. Nevertheless, they are so irrelevant in the model without banking, that even if amplified in the baseline model, they do not gain any importance. This has to be interpreted as follows: if we pick a specification of the SVAR that favors oil supply shocks more, we would see their importance increasing significantly thanks to the accelerator mechanism. Therefore, we can be agnostic in the debate about demand versus supply shocks, because a statistically significant banks' balance-sheet channel exists in any case.

6 Conclusions

The transmission of oil price shocks to the US economy has been scrutinized extensively. Many channels of transmission have been proposed and analyzed. However, very little attention has been given to financial channels, in particular to the effects that oil price shocks can have on banks' balance sheets and to the role that the banking sector can play in transmitting oil price shocks to the real economy. Anecdotal and empirical evidence suggests a pro-cyclical effect of those shocks on banks' balance sheets. In turn, that effect can be at the core of amplification mechanisms that amplify their effect, giving to the banking sector a potential role in characterizing how those shocks transmit to the real economy and how

[27]Our analysis is consistent with Kilian (forthcoming), who reiterates that "[his] analysis reaffirms the conclusion that the one-month oil supply elasticity is close to zero, which implies that oil demand shocks are the dominant driver of the real price of oil", and with Kilian and Zhou (forthcoming), who state that "there is robust evidence that the effect of oil demand shocks on the real price of oil is quantitatively more important than that of oil supply shocks".

relevant they are in explaining business cycle fluctuations.

To account for that, in this paper we set up and estimate a real business cycle dynamic stochastic general equilibrium model with an oil sector, as in Bjornland et al. (2018), and a banking sector as in Gertler and Karadi (2011). Our baseline model embeds the banks' balance-sheet channel. That implies the existence of the financial accelerator mechanism, which is supposed to enhance and amplify the shocks hitting the economy. Hence, our contribution is to propose and formalize the theoretical banks' balance-sheet channel in the context of a structural model, to evaluate it empirically, and to explore the implications for our knowledge of how oil price shocks propagate to the real economy and how relevant they are in explaining business cycle fluctuations.

The main takeaway of our analysis is that the balance-sheet channel plays a crucial role in properly estimating the effects of oil price shocks on the US economy. Ignoring it leads to greatly under-evaluating those effects. All of our results emphatically stress that.

In fact, we find that the financial accelerator mechanism is quantitatively important and statistically significant, meaning that oil price shocks have a bigger effect on the US economy in our baseline model than in a model without banking, thanks to pro-cyclical variations in banks' net worth. This implies, if assessed via variance decomposition, that oil price shocks explain a non-negligible share of GDP growth variability, up to 17 percent in the very short run, and around 13 percent in the medium to long run. On the contrary, in a model with oil only, that percentage would be much lower, around 6-7 percent across all horizons.

The historical decomposition shows that, in our baseline model, oil price shocks were important drivers of the Great Recession, contributing negatively during the first part and positively during the second part from 2008Q4 onward. In the model without banking, they also play a role, but a much smaller one. In an exercise in which we construct a the counterfactual US economy in the absence of oil price shocks, we quantify that the Great Recession's GDP growth trough would have been 2.48 percentage points more negative in 2008Q4 without the beneficial effect of low oil prices. The estimate without the banking sector is only 1.30 percentage points.

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Figures and Tables

Table 1: **Fixed parameters**

Parameter	**Symbol**	**No Oil No Banking (RBC)**	**Oil No Banking**	**No Oil Banking**	**Oil Banking (Baseline)**
		Calibrated Parameters			
Discount Rate	β	0.9959	0.9959	0.9959	0.9959
Inverse Frisch Elasticity of Labor Supply	φ	0.2760	0.2760	0.2760	0.2760
Elasticity of Marginal Depreciation wrt Utilization Rate	ζ	7.2	7.2	7.2	7.2
Labor Share in Production Function	α	0.64	0.64	0.64	0.64
SS Depreciation Rate	$\delta(U)$	0.025	0.025	0.025	0.025
Oil Share	O_y/Y	–	0.039	–	0.039
GDP Quarterly Trend Growth Rate	γ	1.0035	1.0035	1.0035	1.0035
Government Spending to GDP Ratio	G/Y	0.2	0.2	0.2	0.2
SS Gross External Finance Premium	R_k/R	1	1	1.0060	1.0060
SS Bank Leverage	ϕ	–	–	4	4
Proportional Transfer to Entering Bankers	ω	–	–	0.0022	0.0022
Oil Weight in Technology	$1-\omega_k$	0	0.1	0	0.1
		Implied Parameters			
Relative Utility Weight of Labor	χ	5.4498	5.5057	4.9510	5.0476
Utilization Rate Function Parameter I	δ_c	0.0210	0.0210	0.0203	0.0203
Utilization Rate Function Parameter II	b	0.0326	0.0326	0.0387	0.0387
SS Government Expenditure	g	0.2572	0.1744	0.2339	0.1602
SS Private Investment	i	0.4044	0.2445	0.3105	0.1896
SS Survival Rate of Bankers	θ	–	–	0.9640	0.9640
SS Fraction of Capital that Can Be Diverted	λ	–	–	0.7112	0.7112
Elasticity of substitution between oil and capital	$1/\varrho$	–	0.9841	–	0.9836

Notes: The table shows the parameter names, their symbols and their calibrated values. The bottom part of the table presents the parameter values implied by steady state restrictions across different model specifications: RBC model (first column), RBC model plus the oil sector (second column), RBC model plus the banking sector (third column), and our baseline model with both the oil and the banking sectors (fourth column).

Table 2: **Prior and posterior distributions**

Parameter				**No Oil No Banking (RBC)**	**Oil No Banking**	**No Oil Banking**	**Oil Banking (Baseline)**
	Prior	Mean	St. Dev.	Post. Mode	Post. Mode	Post. Mode	Post. Mode
σ_z	IG	0.100	3.00	1.2695	2.3337	1.2268	1.4235
σ_ξ	IG	0.100	3.00	3.0739	5.1498	2.0548	2.2560
σ_g	IG	0.100	3.00	2.9598	3.3318	1.9012	2.1069
σ_θ	IG	0.100	3.00	–	–	0.5287	0.5307
σ_λ	IG	0.100	3.00	–	–	3.0734	2.9233
σ_{P_o}	N	14.859	0.5	–	14.9885	–	14.8534
σ_W	N	0.352	0.5	–	0.3400	–	0.3330
ρ_z	B	0.500	0.20	0.0789	0.2128	0.5640	0.6078
ρ_ξ	B	0.500	0.20	0.0205	0.0264	0.0864	0.0796
ρ_g	B	0.500	0.20	0.8989	0.8863	0.9257	0.8961
ρ_θ	B	0.500	0.20	–	–	0.9631	0.9502
ρ_λ	B	0.500	0.20	–	–	0.9928	0.9890
h	B	0.500	0.20	0.7510	0.8512	0.6317	0.7176
η_i	G	4.000	1.00	0.4493	1.4434	1.0944	1.0592
$b_{1,1}$	N	0.632	0.005	–	0.6311	–	0.6280
$b_{1,2}$	N	-0.126	0.005	–	-0.1256	–	-0.1243
$b_{1,3}$	N	0.003	0.001	–	0.0030	–	0.0030
$b_{1,4}$	N	-0.005	0.001	–	-0.0047	–	-0.0048
$b_{2,1}$	N	4.773	0.005	–	4.7741	–	4.7781
$b_{2,2}$	N	-4.840	0.005	–	-4.8396	–	-4.8397
$b_{2,3}$	N	1.1350	0.005	–	1.1406	–	1.1362
$b_{2,4}$	N	-0.1790	0.005	–	-0.1745	–	-0.1755
$corr(u_t^W, u_t^{P_o})$	N	0.314	0.005	–	0.3127	–	0.3167

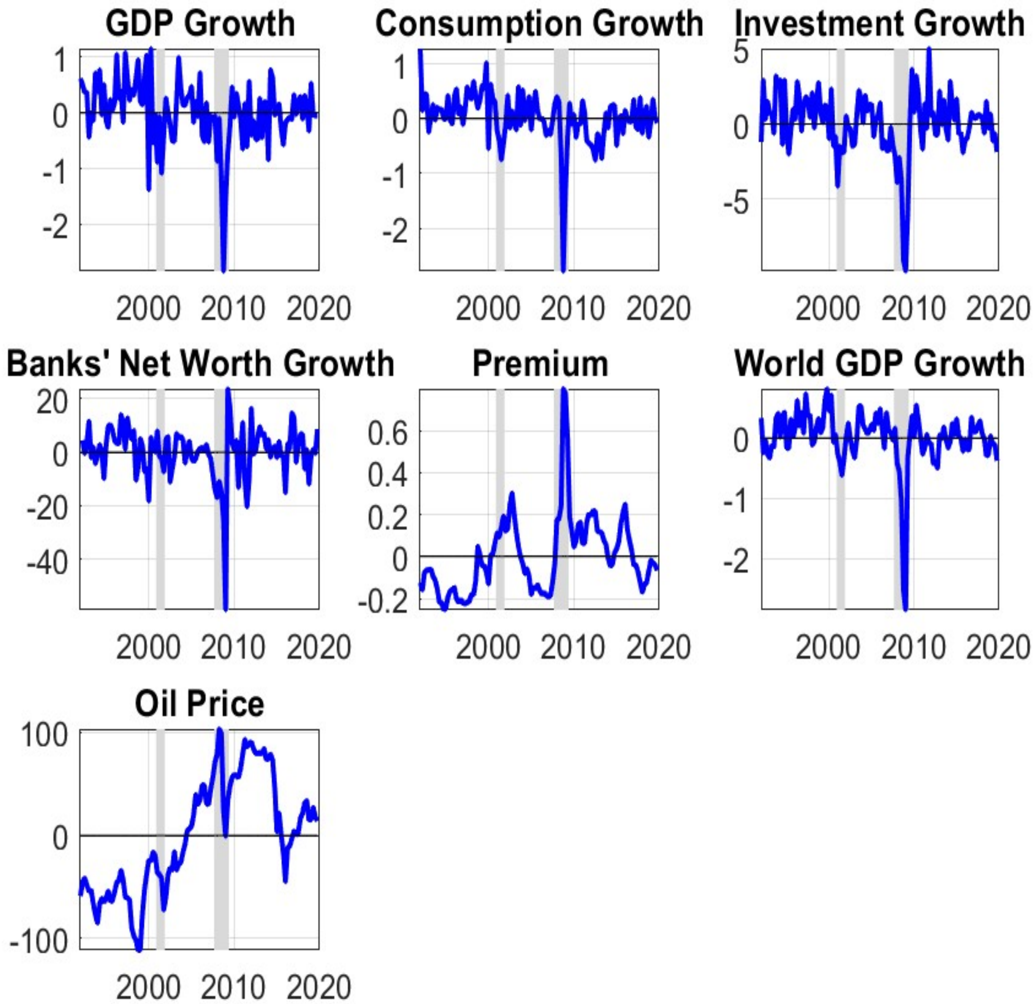
Notes: The table shows the modes of the posterior distributions of the estimated parameters. We also report the means and standard deviations of the prior distributions. Regarding the prior distributions, B, N, G and IG stand for Beta, Normal, Gamma and Inverse Gamma, respectively. Estimates of the parameters are reported across different model specifications: RBC model (first column), RBC model plus the oil sector (second column), RBC model plus the banking sector (third column), and our baseline model with both the oil and the banking sectors (fourth column).

Table 3: **GDP growth variance decomposition**

Shock	**No oil No Banking (RBC)**	**Oil No Banking**	**No Oil Banking**	**Oil Banking (Baseline)**
1 quarter ahead				
Technology, ε_t^z	77.86	75.47	57.25	51.19
Quality of Capital, ε_t^ξ	1.06	0.01	23.97	13.73
Government Spending, ε_t^g	21.08	18.37	6.29	6.27
Divert, ε_t^λ	–	–	12.34	9.94
Banks' Net Worth, ε_t^θ	–	–	0.16	0.10
Oil Price, $\varepsilon_t^{P_o}$	–	5.55	–	16.94
World GDP Growth, ε_t^W	–	0.60	–	1.83
4 quarters ahead				
Technology, ε_t^z	78.40	77.72	69.19	65.88
Quality of Capital, ε_t^ξ	1.10	0.01	16.56	8.81
Government Spending, ε_t^g	20.49	14.53	4.02	3.80
Divert, ε_t^λ	–	–	9.20	6.76
Banks' Net Worth, ε_t^θ	–	–	1.02	0.65
Oil Price, $\varepsilon_t^{P_o}$	–	6.99	–	12.74
World GDP Growth, ε_t^W	–	0.75	–	1.37
16 quarters ahead				
Technology, ε_t^z	78.24	77.70	68.43	66.01
Quality of Capital, ε_t^ξ	1.12	0.03	16.81	8.87
Government Spending, ε_t^g	20.64	14.43	3.80	3.52
Divert, ε_t^λ	–	–	9.12	6.70
Banks' Net Worth, ε_t^θ	–	–	1.84	1.06
Oil Price, $\varepsilon_t^{P_o}$	–	7.07	–	12.50
World GDP Growth, ε_t^W	–	0.76	–	1.35
Infinity				
Technology, ε_t^z	78.21	77.46	68.15	65.70
Quality of Capital, ε_t^ξ	1.15	0.04	16.86	8.88
Government Spending, ε_t^g	20.64	14.39	3.79	3.51
Divert, ε_t^λ	–	–	9.13	6.70
Banks' Net Worth, ε_t^θ	–	–	2.07	1.21
Oil Price, $\varepsilon_t^{P_o}$	–	7.33	–	12.64
World GDP Growth, ε_t^W	–	0.79	–	1.36

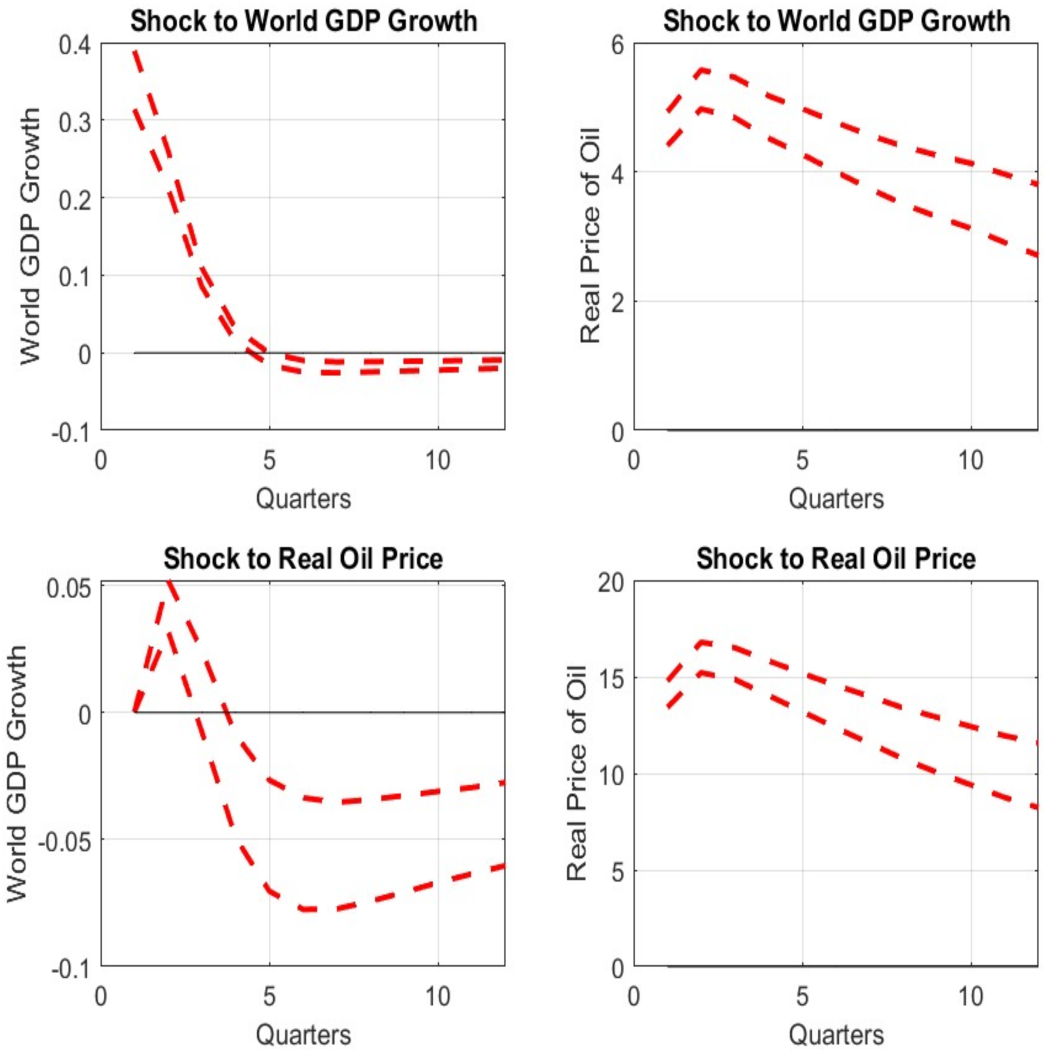
Notes: The table shows the real per capita GDP growth variance decomposition for different horizons and different model specifications: RBC model (first column), RBC model plus the oil sector (second column), RBC model plus the banking sector (third column), and our baseline model with both the oil and the banking sectors (fourth column). The variance decomposition is computed at the posterior modes.

Figure 1: **Transformed data used in the estimation**



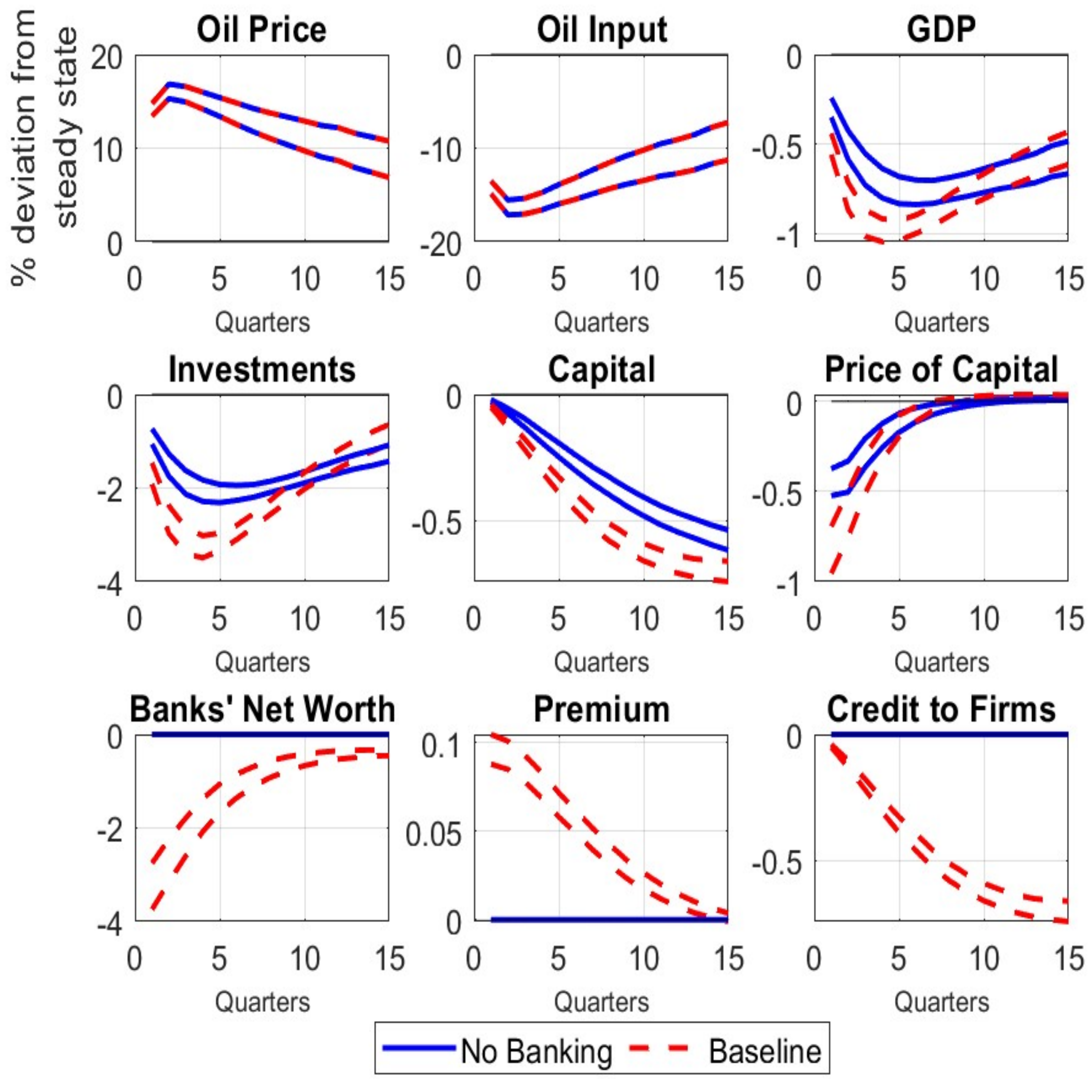
Notes: In the graphs above, the blue lines indicate the observed data used to estimate our model, whereas the gray areas are the US recessions as identified by the NBER. The sample is 1992Q1:2019Q4.

Figure 2: **Oil sector SVAR dynamics**



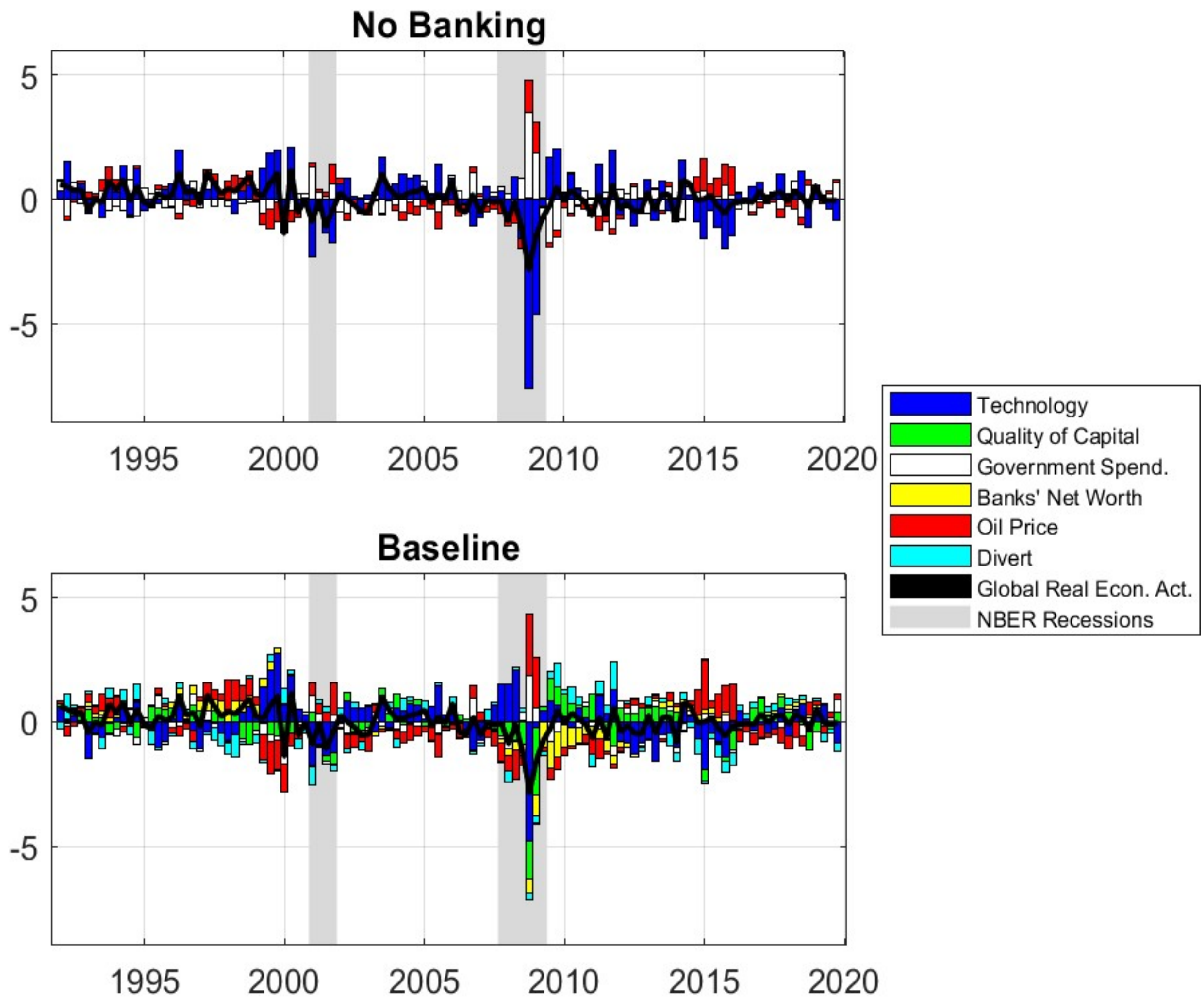
Notes: The figure shows the impulse response functions of the growth rate of world GDP and of the real price of oil to an estimated one standard deviation shock to world GDP growth and to the real price of oil, respectively. The graphs report the 5*th* and 95*th* percentiles of the responses for each variable.

Figure 3: **Oil price shock dynamics**



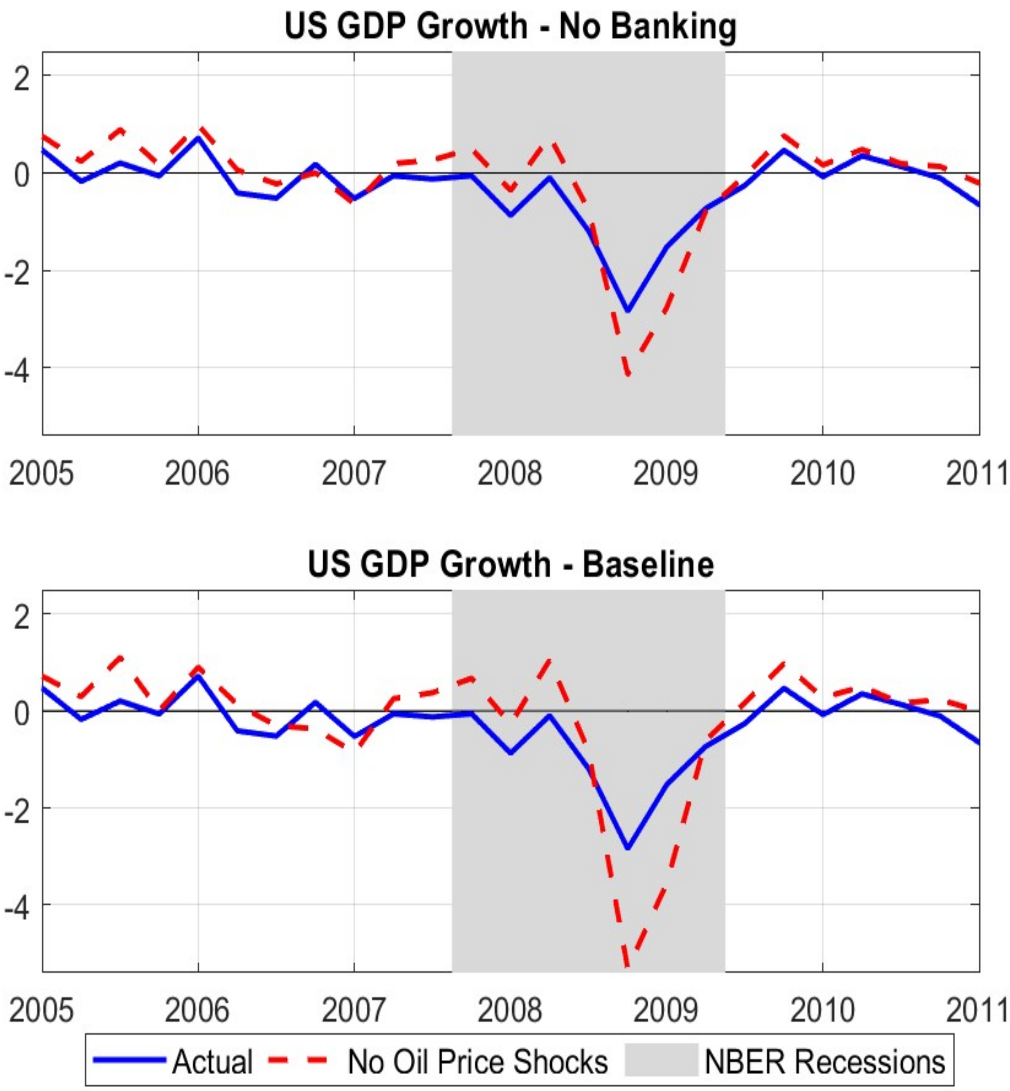
Notes: The figure shows the impulse response functions of the key variables to an estimated one standard deviation shock to the real oil price. The graphs report the $5th$ and $95th$ percentiles of the responses for each variable. The solid blue lines indicate an RBC model with oil only, whereas dashed red lines correspond to our baseline model.

Figure 4: **US GDP growth historical decomposition**



Notes: The figure shows the US real per capita GDP growth historical decomposition. In the top panel, we report the real business cycle model with oil, whereas in the bottom panel we show our baseline model. Bars of different colors indicate the several shocks in the model, and the gray areas are the US recessions as identified by the NBER.

Figure 5: **Counterfactual GDP growth – Zooming in on the Great Recession**



Notes: The figure shows a counterfactual analysis. The blue lines represent the actual observed US real per capita GDP growth, while the red lines show the counterfactual level of the US real per-capita GDP growth that would have prevailed in the absence of oil price shocks. In the top panel, we report the real business cycle model with oil; in the bottom panel we show our baseline model.

Appendices

A Data

As we described in the main body of the paper, the data are quarterly and the model is estimated for the sample period 1992:Q1-2019:Q4. In this appendix we provide the original sources and construction methods of the observed series.

Real GDP is released by the US BEA (Real Gross Domestic Product [GDPC1], downloaded from https://fred.stlouisfed.org/series/GDPC1). The series of nominal personal consumption expenditures is the sum of personal consumption expenditures of non-durable goods released by the US BEA (Personal Consumption Expenditures: Non-durable Goods [PCND], downloaded from https://fred.stlouisfed.org/series/PCND) and personal consumption expenditures of services released by the US BEA (Personal Consumption Expenditures: Services [PCESV], downloaded from https://fred.stlouisfed.org/series/PCESV). The series of nominal private investment is the sum of personal consumption expenditures of durable goods released by the US BEA (Personal Consumption Expenditures: durable Goods [PCDG], downloaded from https://fred.stlouisfed.org/series/PCDG) and gross private domestic investment released by the US BEA (Gross Private Domestic Investment [GPDI], downloaded from https://fred.stlouisfed.org/series/GPDI). The civilian non-institutional population is released by the US BLS (Population Level [CNP16OV], downloaded from https://fred.stlouisfed.org/series/CNP16OV) and is transformed in LNSINDEX. The annualized Moody's Seasoned Baa Corporate Bond Yield spread over the 10-Year Treasury Note Yield at Constant Maturity is 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], downloaded from https://fred.stlouisfed.org/series/BAA10Y). The DJGL US banks' stock market index is taken from https://markets.businessinsider.com/index/historical-prices/dow-jones-us-banks. The GDP deflator is released by the US BEA (Gross Domestic Product: Implicit Price Deflator [GDPDEF], downloaded from https://fred.stlouisfed.org/series/GDPDEF). Let Δ denote the temporal difference operator.

Then the variables are transformed as follows:

$$\text{Output growth} = 100\Delta LN(GDPC1/LNSINDEX)$$
$$\text{Consumption growth} = 100\Delta LN(((PCND + PCESV)/GDPDEF)/LNSINDEX)$$
$$\text{Investment growth} = 100\Delta LN(((PCDG + GPDI)/GDPDEF)/LNSINDEX)$$
$$\text{Spread} = (1/4) * (BAA\ CORPORATE - 10\ YEAR\ TREASURY)$$
$$\text{Net worth growth} = 100\Delta LN((DJGL/GDPDEF)/LNSINDEX)$$

The remaining series are related to the oil market. For world activity we use quarterly GDP growth (percentage change) for the OECD countries. The series is downloaded from OECD (https://data.oecd.org/gdp/quarterly-gdp.htm#indicator-chart). The real price of oil ($P_{o,t}$) is expressed in log terms. This series is obtained from the refiner acquisition cost of imported crude oil. The source is the US Department of Energy (http://www.eia.gov/dnav/pet/pet_pri_rac2_dcu_nus_m.htm). The nominal series of the oil price is deflated by the Personal Consumption Expenditures Chain-type Price Index [PCEPI], downloaded from https://fred.stlouisfed.org/series/PCEPI.

Finally, the series used in the robustness analysis. The Kilian index of global real economic activity is based on dry cargo single-voyage ocean freight rates. The source of this series is Kilian's website (https://sites.google.com/site/lkilian2019/research/data-sets). The GECON index is based on a set of 16 indicators that cover a broad range of variables tied to energy demand. The variables represent different data categories spanning multiple dimensions of the global economy: real economic activity, commodity prices, financial indicators, transportation, uncertainty, expectations, weather, and energy-related measures. Baumeister et al. (2022) extract the first principal component from this unbalanced panel of 16 variables by applying the EM algorithm recursively. The source of this series is Baumeister's website (https://sites.google.com/site/cjsbaumeister/research). Global oil production is obtained from world crude oil production in millions per barrels pumped per day (averaged by month). We compute the growth rate of the resulting series. The source is the US Department of Energy (https://www.eia.gov/international/data).

B The Stationary System

To get a stationary system we use the following variable transformations: $c_t = \frac{C_t}{Z_t}$, $\psi_t = \Psi_t Z_t$, $y_t = \frac{Y_t}{Z_t}$,$a_t = \frac{A_t}{Z_t}$ $k_t = \frac{K_t}{Z_t}$, $o_{y,t} = \frac{O_{y,t}}{Z_t}$, $w_t = \frac{W_t}{Z_t}$, $i_{n,t} = \frac{I_{n,t}}{Z_t}$, $i_t = \frac{I_{,t}}{Z_t}$, $n_t = \frac{N_t}{Z_t}$, $n_{e,t} = \frac{N_{e,t}}{Z_t}$, $n_{n,t} = \frac{N_{n,t}}{Z_t}$, $f_t = \frac{F_t}{Z_t}$. With these definitions the stationary system is as follows.

The marginal utility of consumption is given by:

$$\psi_t = \left[\left(c_t - h\frac{c_{t-1}}{e^{z_t}}\right)\right]^{-1} - \beta h \left[(c_{t+1}e^{z_{t+1}} - hc_t)\right]^{-1} \tag{43}$$

The Euler equation is given by:

$$\beta \frac{\psi_{t+1}}{\psi_t e^{z_{t+1}}} R_{t+1} = 1$$

The labor market equilibrium is given by:

$$\chi L_t^{\varphi} = \psi_t \varrho \alpha \frac{y_t}{L_t} \tag{44}$$

The value of banks' capital is given by:

$$V_t = E_t \left\{ (1-\theta_t)\beta \frac{\psi_{t+1}}{\psi_t e^{z_{t+1}}} (R_{kt+1} - R_{t+1}) + \beta \frac{\psi_{t+1}}{\psi_t} \theta_{t+1} \frac{\phi_{t+1}}{\phi_t} f_{t,t+1} V_{t+1} \right\}$$

The value of banks' net wealth is given by:

$$\eta_t = E_t \left\{ (1-\theta_t) + \beta \frac{\psi_{t+1}}{\psi_t} \theta_{t+1} f_{t,t+1} \eta_{t+1} \right\}$$

The optimal leverage is given by:

$$\phi_t = \frac{\eta_t}{\lambda_t - V_t}$$

The growth rate of banks' capital is given by:

$$f_{t,t+1} e^{z_{t+1}} = (R_{k,t+1} - R_{t+1}) \phi_t + R_{t+1}$$

The growth rate of banks' net wealth is given by:

$$X_{t,t+1} = \frac{\phi_{t+1}}{\phi_t} f_{t,t+1} e^{z_{t+1}}$$

The aggregate capital is given by:

$$Q_t k_{t+1} e^{z_{t+1}} = \phi_t n_t$$

Banks' net worth is given by:

$$n_t = n_{e,t} + n_{n,t}$$

Existing banks' net worth accumulation is given by:

$$n_{e,t} = \theta_t \left[\left(R_{k,t} - R_t \right) \phi_{t-1} + R_t \right] \frac{n_{t-1}}{e^{z_t}}$$

New banks' net worth is given by:

$$n_{n,t} = \omega Q_t \xi_t k_t$$

The production function of final-goods-producing firms is given by:

$$y_t = L_t^{\alpha} \left[\omega_k \left(U_t \xi_t k_t \right)^{1-\varrho} + \left(1 - \omega_k \right) o_{y,t}^{1-\varrho} \right]^{\frac{1-\alpha}{1-\varrho}} \tag{45}$$

The FOC for U_t is given by:

$$\left(1 - \alpha \right) \omega_k \frac{y_t}{U_t^{\varrho}} \left(\frac{\xi_t k_t}{a_t} \right)^{1-\varrho} = b U_t^{\zeta} \xi_t k_t \tag{46}$$

where

$$a_t = \left[\omega_k \left(U_t \xi_t k_t \right)^{1-\varrho} + \left(1 - \omega_k \right) o_{y,t}^{1-\varrho} \right]^{\frac{1}{1-\varrho}} \tag{47}$$

The FOC for W_t

$$w_t = \alpha \frac{y_t}{L_t} \tag{48}$$

The return to capital:

$$R_{k,t+1} = \frac{\xi_{t+1} \left[\left(1 - \alpha \right) \omega_k \frac{y_{t+1}}{\xi_{t+1} \left(e^{z_{t+1}} k_{t+1} \right)^{\varrho}} \left(\frac{U_{t+1} \xi_{t+1}}{e^{z_{t+1}} a_{t+1}} \right)^{1-\varrho} + Q_{t+1} - \delta \left(U_{t+1} \right) \right]}{Q_t} \tag{49}$$

The FOC for $O_{y,t}$ is given by:

$$P_{o,t} = (1-\alpha)(1-\omega_k)\frac{y_t}{o_{y,t}^{\varrho}}\frac{1}{(a_t)^{1-\varrho}} \tag{50}$$

The optimal investment decision is given by:

$$\begin{aligned} Q_t = 1 + \frac{\eta_i}{2}\left(\frac{i_{n,t}+i}{\frac{i_{n,t-1}}{e^{z_t}}+i} - e^z\right)^2 + \eta_i\left(\frac{i_{n,t}+i}{\frac{i_{n,t-1}}{e^{z_t}}+i} - e^z\right)\frac{i_{n,t}+i}{\frac{i_{n,t-1}}{e^{z_t}}+i} \\ - \beta\frac{\psi_{t+1}}{\psi_t e^{z_{t+1}}}\eta_i\left(\frac{i_{n,t+1}+i}{\frac{i_{n,t-1}}{e^{z_t}}+i} - e^z\right)\left(\frac{i_{n,t+1}e^{z_{t+1}}+i}{i_{n,t}+i}\right)^2 \end{aligned}$$

The depreciation rate is given by:

$$\delta(U_t) = \delta_c + \frac{b}{1+\zeta}U_t^{1+\zeta}$$

The net investment is given by:

$$i_{n,t} = i_t - \delta(U_t)\xi_t k_t$$

The capital accumulation equation is given by:

$$k_{t+1}e^{z_{t+1}} = \xi_t k_t + i_{n,t} \tag{51}$$

The aggregate resource constraint is given by:

$$y_t = P_{o,t}o_{y,t} + c_t + i_t + G_t + \frac{\eta_i}{2}\left(\frac{i_{n,t}+i}{\frac{i_{n,t-1}}{e^{z_t}}+i} - e^z\right)^2(i_{n,t}+i) \tag{52}$$

The technology shock is given by:

$$\begin{aligned} \frac{Z_t}{Z_{t-1}} &= e^{z_t} \\ (z_t) &= (1-\rho_z)\gamma + \rho_z(z_{t-1}) + \sigma_z\varepsilon_t^z \end{aligned}$$

The quality of capital shock is given by:

$$\ln(\xi_t) = (1-\rho_\xi)\ln\xi + \rho_\xi\ln(\xi_{t-1}) + \sigma_\xi\varepsilon_t^\xi$$

The government spending shock:

$$\ln(G_t) = (1 - \rho_g) \ln g + \rho_g \ln(G_{t-1}) + \sigma_g \varepsilon_t^g$$

The net worth shock is given by:

$$\ln(\theta_t) = (1 - \rho_\theta) \ln \theta + \rho_\theta \ln(\theta_{t-1}) + \sigma_\theta \varepsilon_t^\theta$$

The divert shock is given by:

$$\ln(\lambda_t) = (1 - \rho_\lambda) \ln \lambda + \rho_\lambda \ln(\lambda_{t-1}) + \sigma_\lambda \varepsilon_t^\lambda$$

C Steady State

In this appendix we compute the steady state of the baseline stationary model. Some values are set as follows: $U = 1$, $\delta(U) = 0.025$, $Q = 1$, $R_k/R = 1.006$, $z = \gamma = 1.0035, P_o = 1$.

From the Euler equation

$$R = \frac{e^z}{\beta}$$

From the final production good firms FOCs

$$b = \frac{R_k}{R}R - 1 + \delta$$

Assuming $L = 1/3$, we solve numerically and simultaneously equations (43), (44), (45), (46), (47), (48), (49), (50), (51), and (52), and $\frac{O_y}{Y} = 0.039$. Eleven equations for the following eleven unknowns: $y, k, \chi, i, c, \psi, R_k, w, o_y, a, \varrho$.

Government spending

$$g = \frac{g}{y}y$$

From the depreciation rate equation

$$\delta_c = \delta(U) - \frac{b}{1+\zeta}$$

We set the intermediaries' leverage ratio $\phi = 4$. Therefore, banks' variables and parameters are as follows

$$f = \frac{(R_k - R)\phi + R}{e^z}$$

$$x = fe^z$$

$$\theta = \frac{1 - \frac{\phi\omega}{e^z}}{f}$$

$$\nu = \frac{(1-\theta)\beta(R_k - R)}{e^z(1-\beta\theta f)}$$

$$\eta = \frac{1-\theta}{1-\beta\theta f}$$

$$\lambda = \frac{\eta}{\phi} + \nu$$

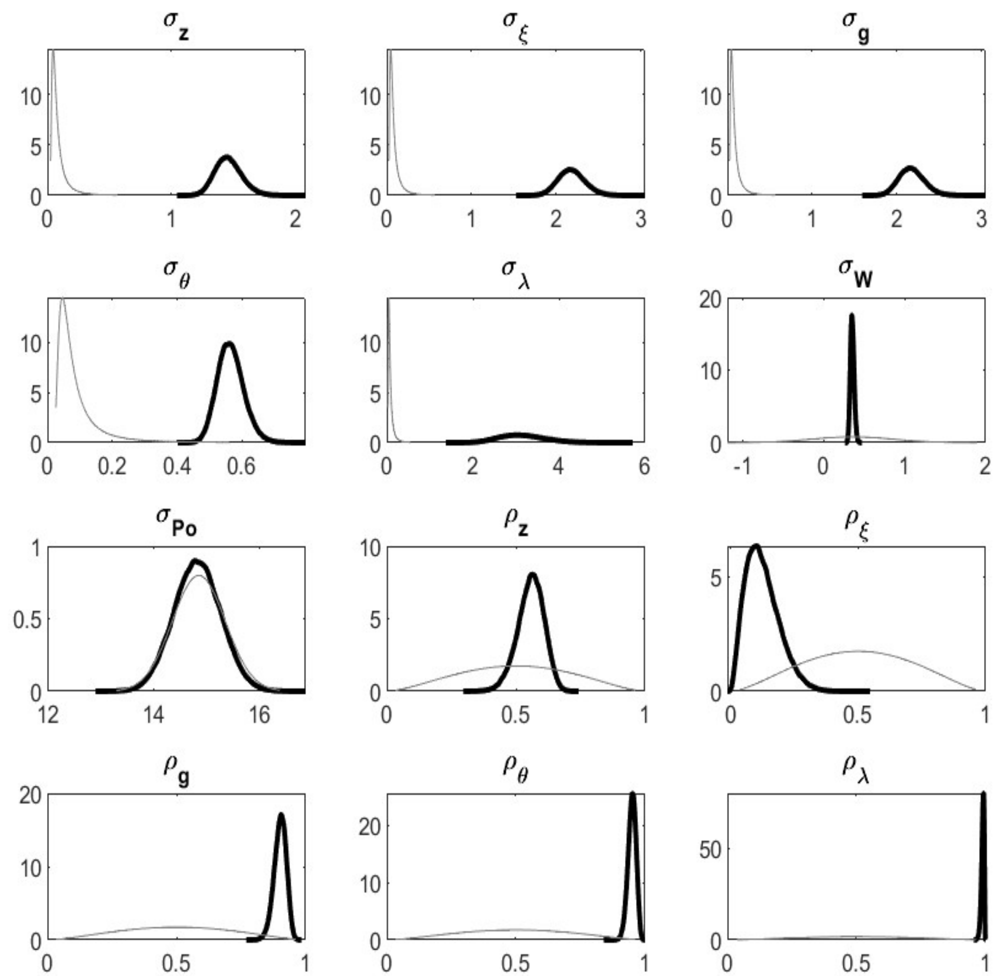
$$n = \frac{k}{\phi}$$

$$n_e = \theta f N$$

$$n_n = \frac{\omega k}{e^z}$$

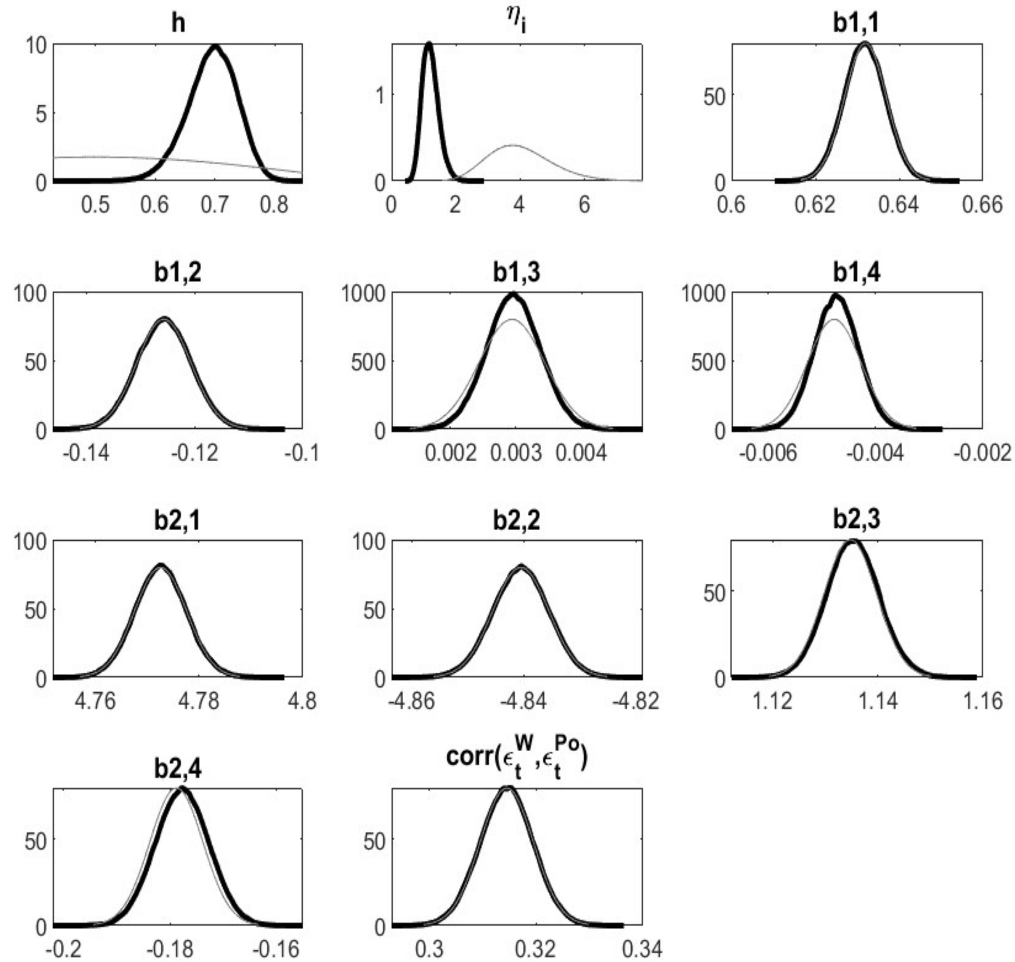
D Prior and Posterior Distributions

Figure D1: **Prior and posterior distributions.**



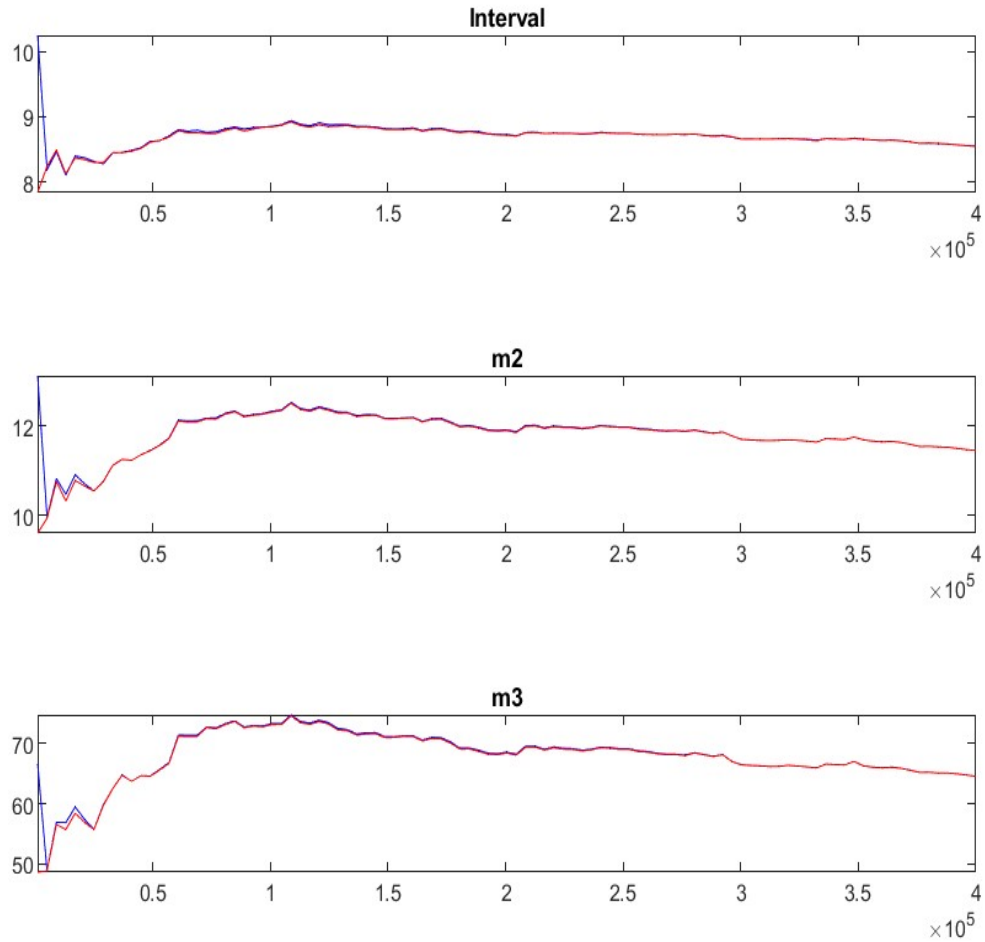
Notes: In the graphs above, the thin gray lines represent the prior distributions and the thick dark lines correspond to the posterior distributions.

Figure D2: **Prior and posterior distributions.**



Notes: In the graphs above, the thin gray lines represent the prior distributions and the thick dark lines correspond to the posterior distributions.

Figure D3: Brooks and Gelman (1998) **convergence diagnostics**



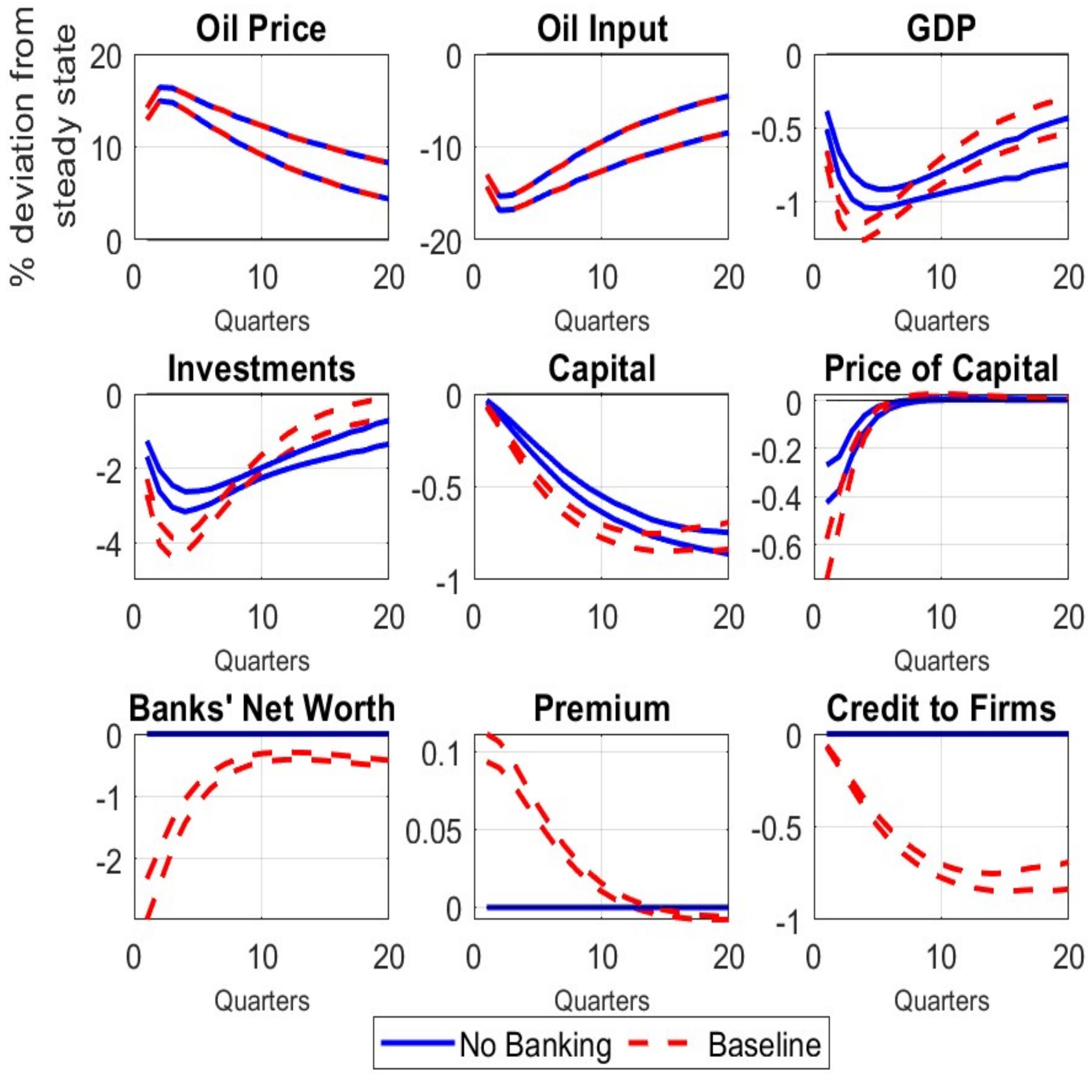
Notes: In the graphs above, the red and blue lines represent specific measures of the parameter vectors both within and between chains. First panel: constructed from an 80 percent confidence interval around the parameter mean. Second panel: a measure of the variance. Third panel: based on third moments. The overall convergence measures are constructed on an aggregate measure based on the eigenvalues of the variance-covariance matrix of each parameter.

E Robustness

Here, we report the robustness tests that we described in the main text. We follow the same order as we use in the text. All the other figures and tables are available upon request.

Long Sample

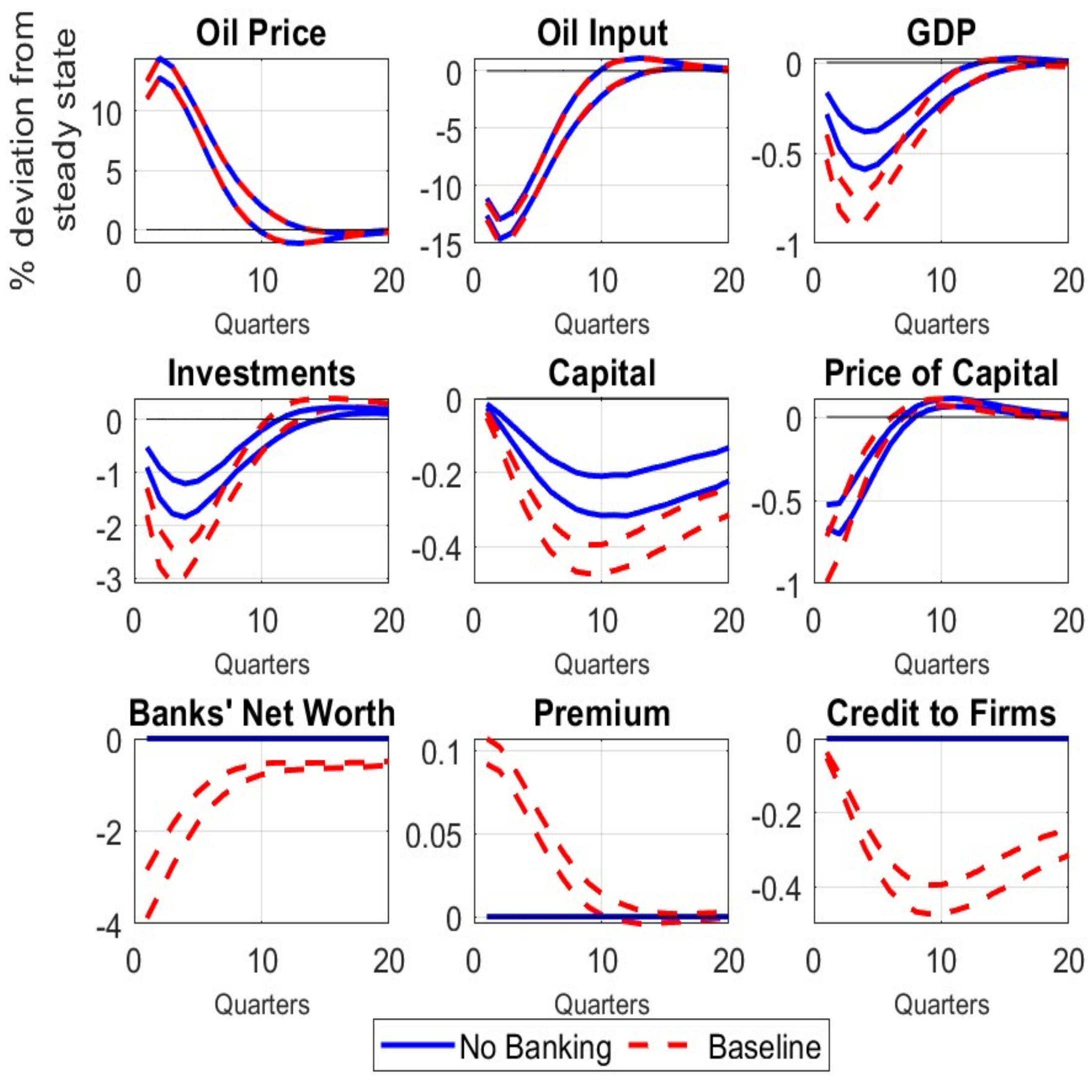
Figure E1: **Oil price shock dynamics**



Notes: The figure shows the impulse response functions of the key variables to an oil price shock. The graphs report the 5*th* and 95*th* percentiles of the responses for each variable. The solid blue lines indicate an RBC model with oil only, whereas the dashed red lines correspond to our baseline model. Sample 1974-2019.

Stationarity of the oil price

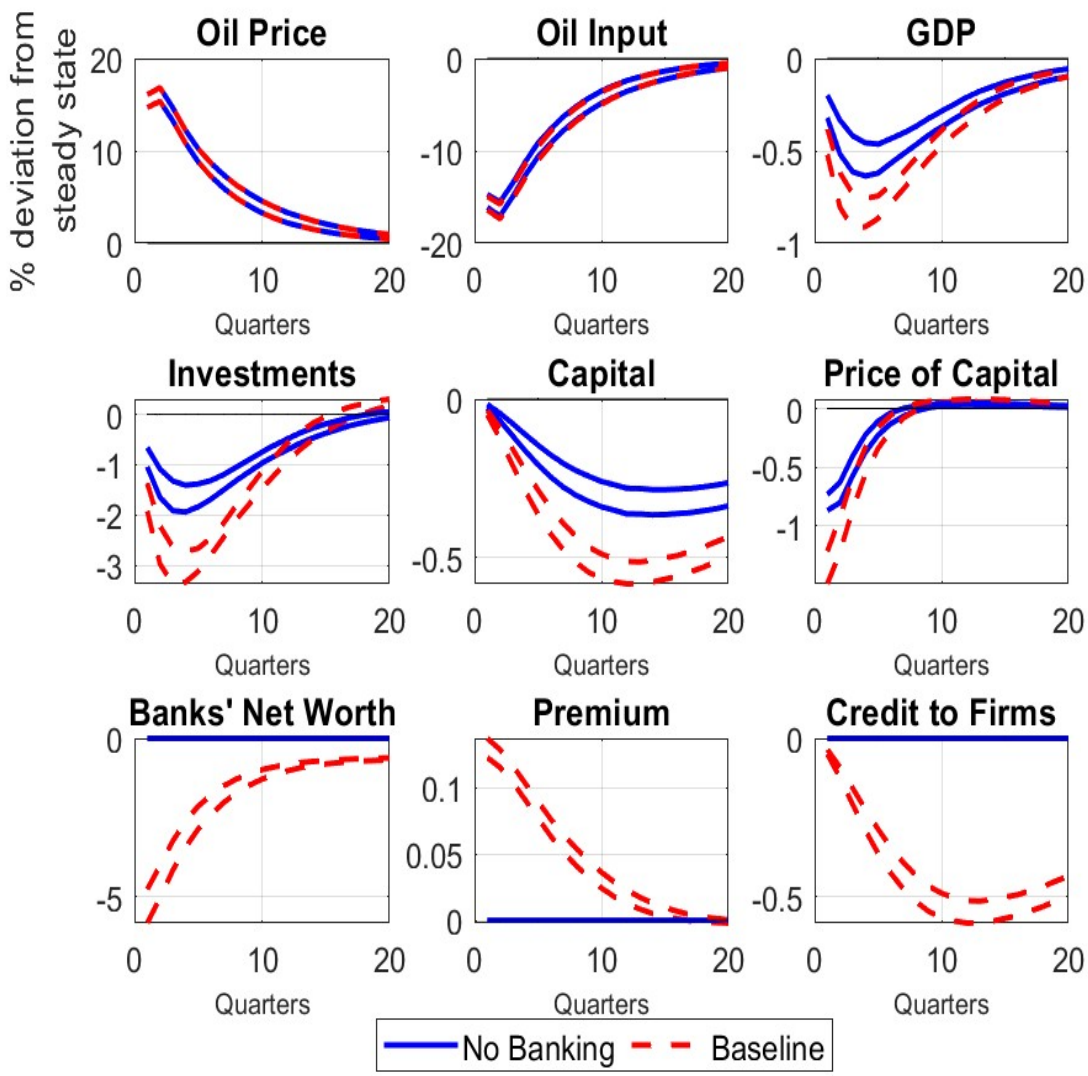
Figure E2: **Oil price shock dynamics (sample 1992Q1–2004Q4)**



Notes: The figure shows the impulse response functions of the key variables to an oil price shock. The graphs report the 5*th* and 95*th* percentiles of the responses for each variable. The solid blue lines indicate an RBC model with oil only, whereas the dashed red lines correspond to our baseline model. Sample 1992Q1-2004Q4

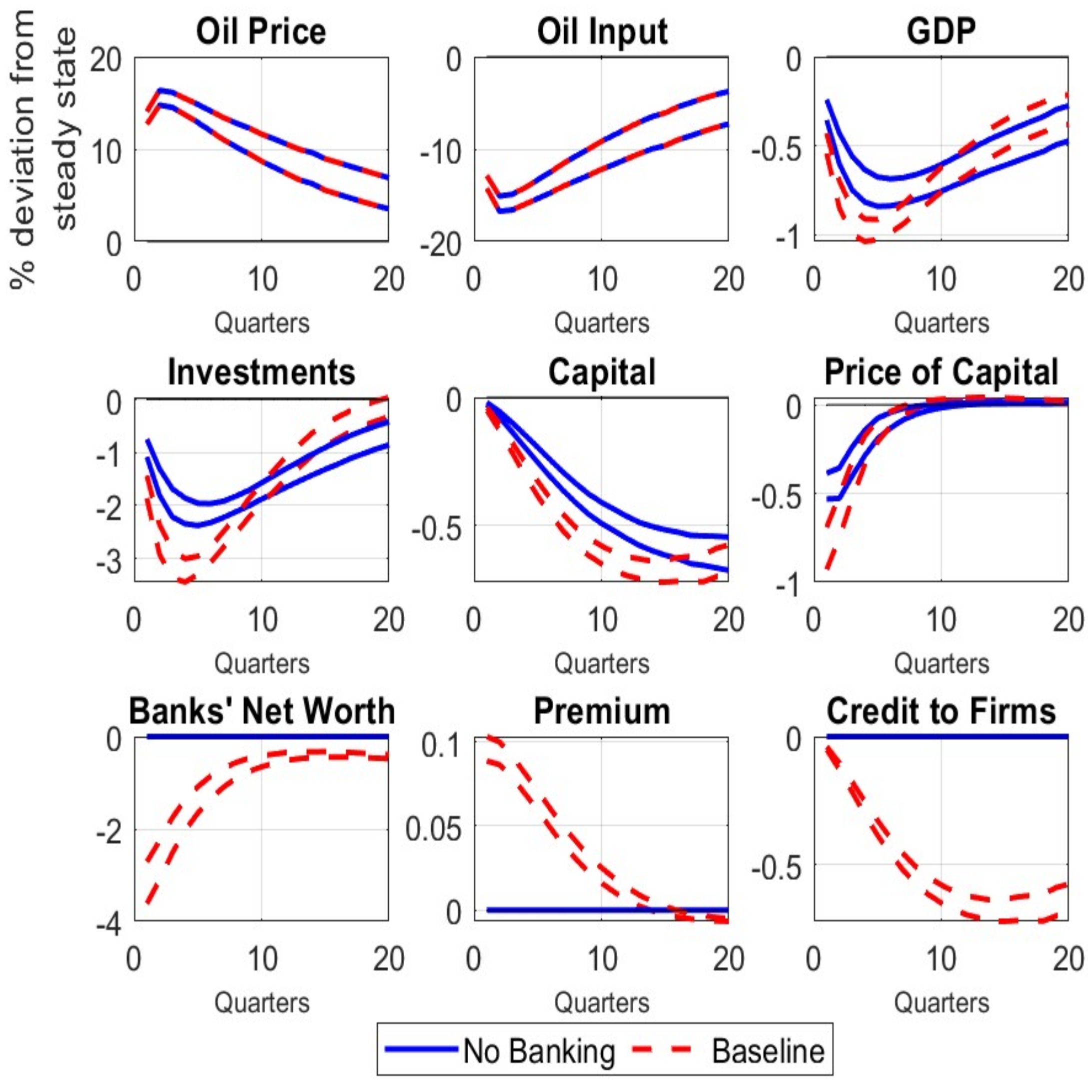
Observables

Figure E3: **Oil price shock dynamics (sample 2005Q1–2019Q4)**



Notes: The figure shows the impulse response functions of the key variables to an oil price shock. The graphs report the $5th$ and $95th$ percentiles of the responses for each variable. The solid blue lines indicate an RBC model with oil only, whereas the dashed red lines correspond to our baseline model. Sample 2005Q1-2019Q4.

Figure E4: **Oil price shock dynamics (Kilian Index)**



Notes: The figure shows the impulse response functions of the key variables to an oil price shock. The graphs report the $5th$ and $95th$ percentiles of the responses for each variable. The solid blue lines indicate an RBC model with oil only, whereas the dashed red lines correspond to our baseline model. We use the Kilian index as in Kilian (2009) as a measure of world economic activity.

Frequency

The mixed-frequency estimation requires properly specifying the measurement equations for the observed variables. Spread, net worth, GDP growth, and consumption growth are available at a monthly frequency.[28] Their measurement equations look like those for the quarterly estimation. For investment growth, available only quarterly, we need to define first the quarterly variable in monthly terms, within a model in which t corresponds to one month. It is the sum of three monthly observations in the quarter. Therefore, the stationary definition for investments is given by:

$$i_t^q = i_t + \frac{i_{t-1}}{e^{z_t}} + \frac{i_{t-2}}{e^{z_t} e^{z_{t-1}}}$$

That variable is observed every three months. So, quarterly investment growth in monthly terms is given by:

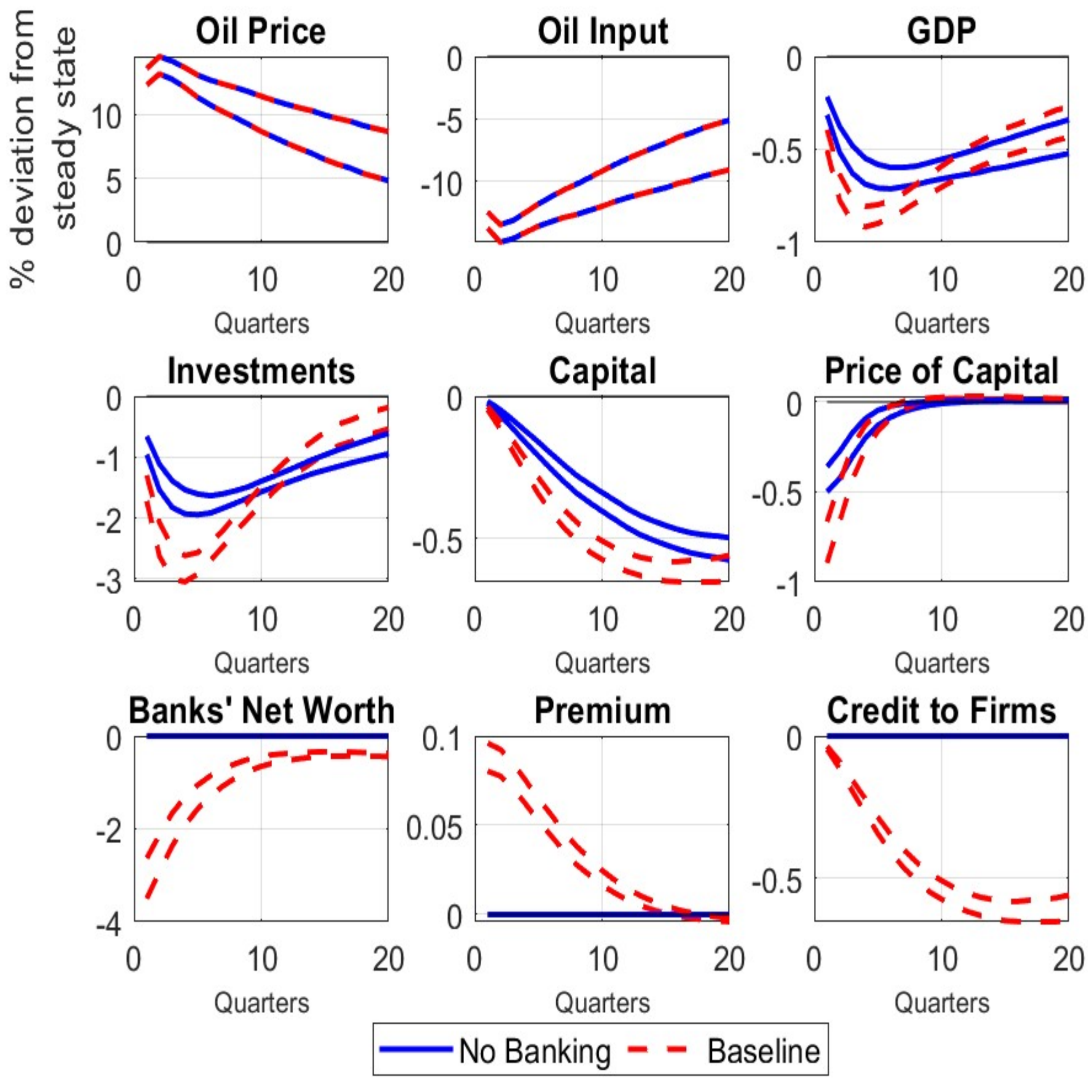
$$\text{Investment growth}^q = \ln\left(i_t^q\right) - \ln\left(i_{t-3}^q\right) + z_t + z_{t-1} + z_{t-2}$$

As for the oil market SVAR, the real oil price is available at a monthly frequency, while world GDP is not. We use the GECON index instead. We estimate the SVAR with 6 lags.

[28]In principle GDP is not available at a monthly frequency. We use the IHS monthly GDP index, which is conceptually consistent with real gross domestic product in the National Income and Product Accounts. Aggregating the data at a quarterly frequency and computing the growth rate deliver the same growth rate computed with quarterly data.

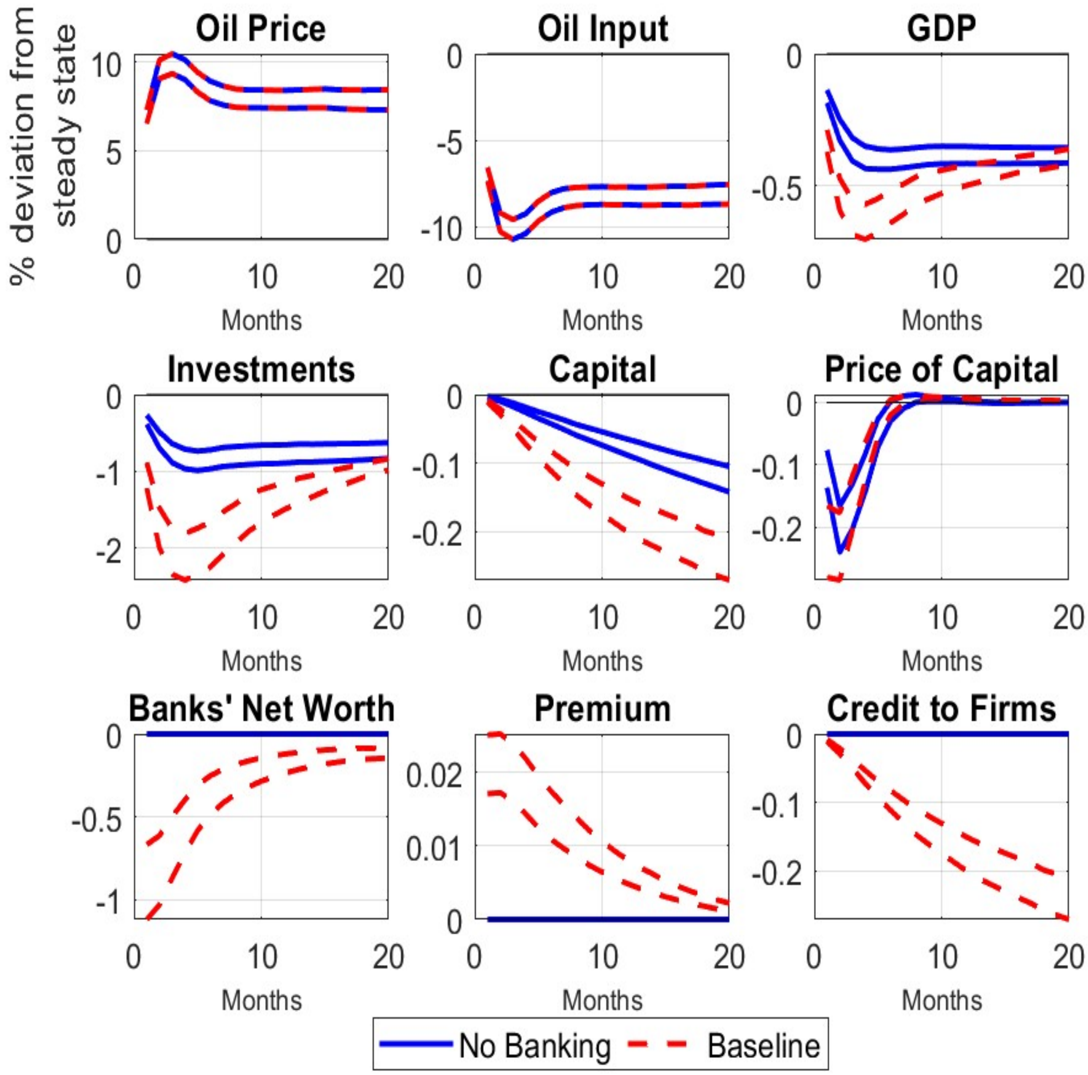
SVAR specification

Figure E5: **Oil price shock dynamics (GECON Index)**



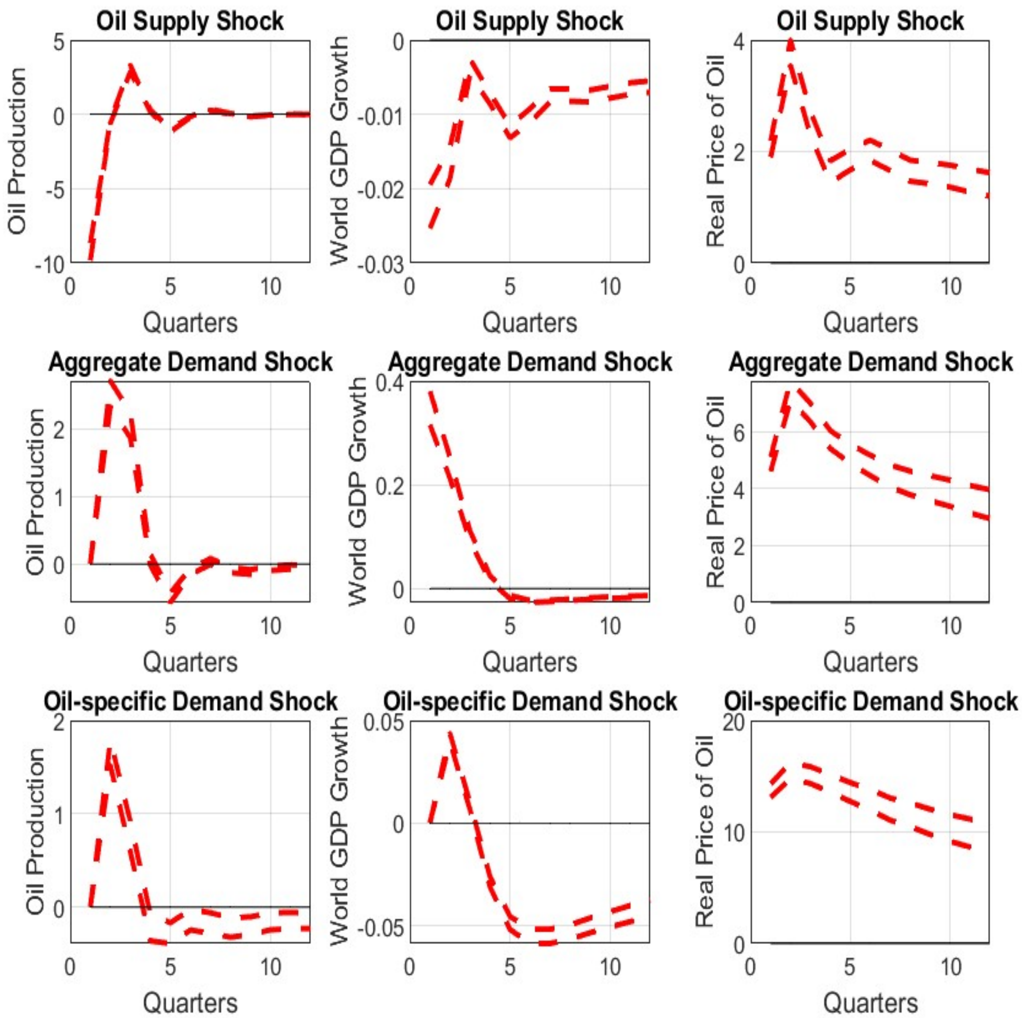
Notes: The figure shows the impulse response functions of the key variables to an oil price shock. The graphs report the $5th$ and $95th$ percentiles of the responses for each variable. The solid blue lines indicate an RBC model with oil only, whereas the dashed red lines correspond to our baseline model. We use the GECON index developed in Baumeister et al. (2022) as a measure of world economic activity.

Figure E6: **Oil price shock dynamics**



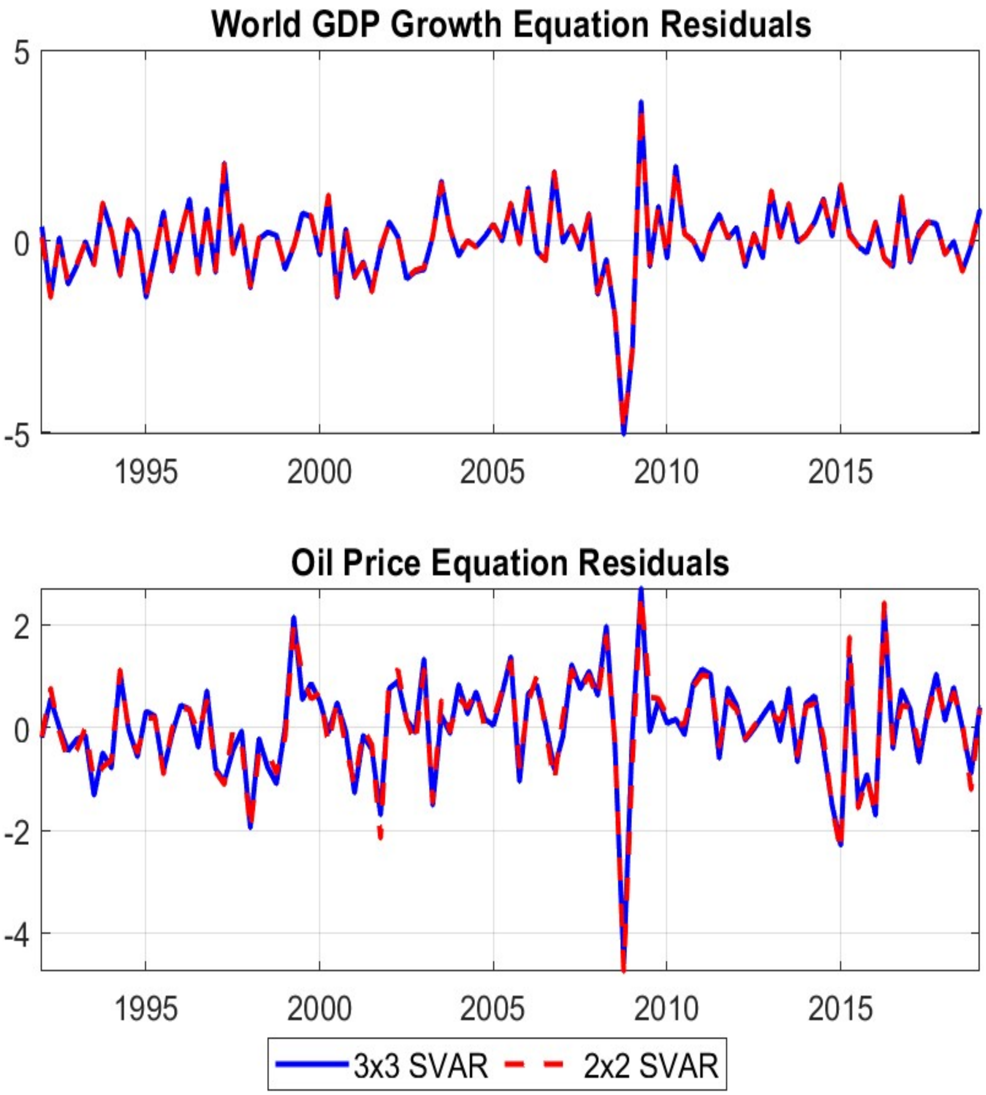
Notes: The figure shows the impulse response functions of the key variables to an oil price shock. The graphs report the $5th$ and $95th$ percentiles of the responses for each variable. The solid solid lines indicate an RBC model with oil only, whereas the dashed red lines correspond to our baseline model.

Figure E7: **Oil sector SVAR dynamics**



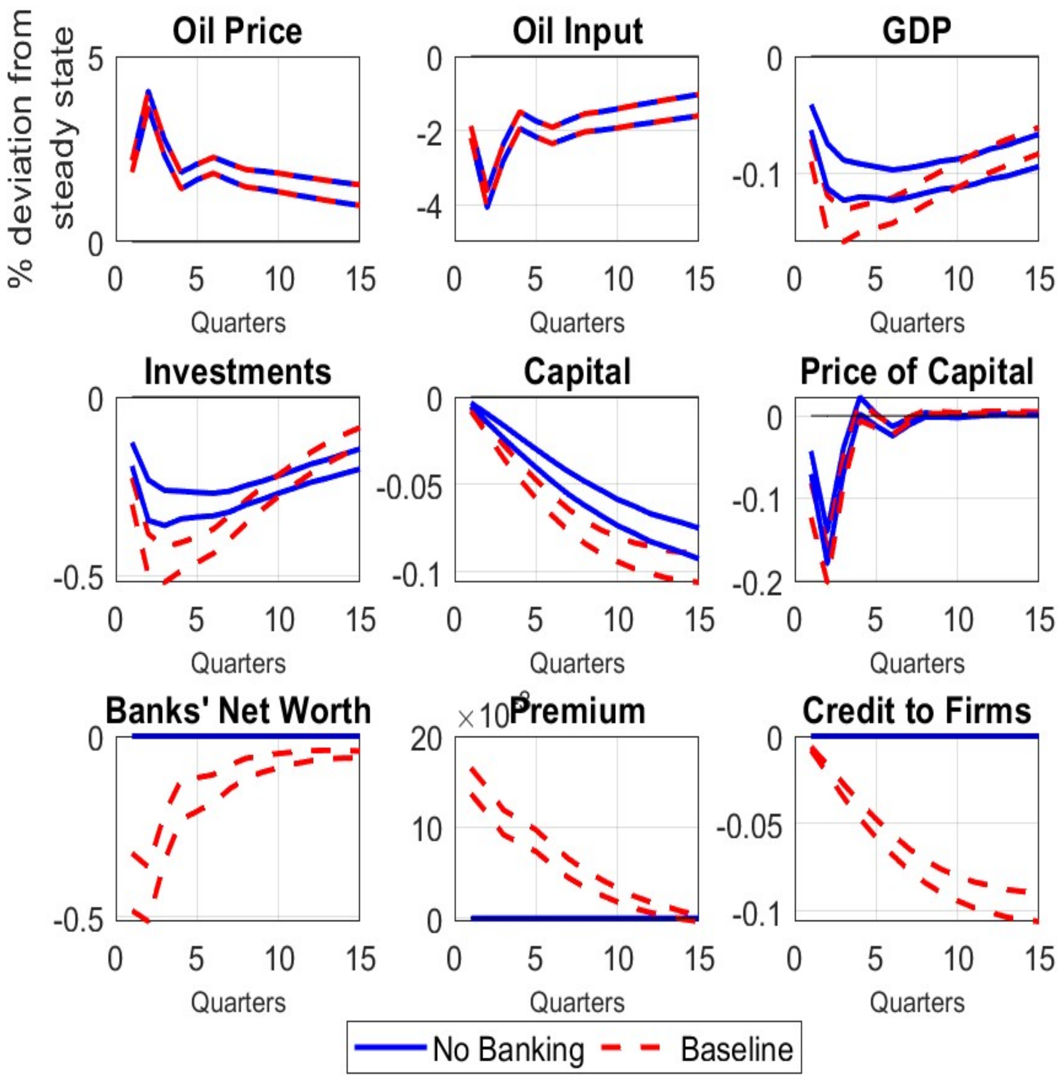
Notes: The figure shows the impulse response functions of oil production, real economic activity and the real price of oil to an oil supply shock, an aggregate demand shock and an oil-specific demand shock, respectively. The graphs report the $5th$ and $95th$ percentiles of the responses for each variable.

Figure E8: **Estimated SVAR residuals**



Notes: The figure shows the estimated residuals of the world GDP growth equation and of the oil price equation in the 2x2 SVAR, estimated with world GDP growth and the real oil price, and in the 3x3 SVAR, estimated with oil production, world GDP growth, and the real oil price.

Figure E9: **Oil supply shocks dynamics**



Notes: The figure shows the impulse response functions of the key variables to an estimated one standard deviation shock to the oil supply. The graphs report the $5th$ and $95th$ percentiles of the responses for each variable. The solid blue lines indicate an RBC model with oil only, and the dashed red lines correspond to our baseline model.