Federal Reserve Bank of Cleveland Working Paper Series

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Working Paper No. 22-33R

October 2024

Suggested citation: Gelain, Paolo and Marco Lorusso. 2024. "Oil Price Fluctuations, US Banks, and Macroprudential Policy." Working Paper No. 22-33R. Federal Reserve Bank of Cleveland. https://doi.org/10.26509/frbc-wp-202233r.

Federal Reserve Bank of Cleveland Working Paper Series
ISSN: 2573-7953

Oil Price Fluctuations, US Banks, and Macroprudential Policy*

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October 16, 2024

Abstract

Using US micro-level data on banks, we document a negative effect of high oil prices on US banks' balance sheets, more negative for highly leveraged banks. We set and estimate a general equilibrium model with banking and oil sectors that rationalizes those findings through the financial accelerator mechanism. This mechanism amplifies the effect of oil price shocks, making them non-negligible drivers of the dynamics of US banks' intermediation activity and of the US real economy. Macroprudential policy, in the form of a countercyclical capital buffer, can meaningfully address oil price fluctuations and reduce the volatility they cause in the US economy.

Keywords: Oil price shocks, DSGE models, Financial frictions, Macroprudential policy
JEL classification: E32, E44, Q35, Q43

*We are particularly thankful to Michael Plante for his very helpful discussion at the 2021 System Energy Meeting. We would also like to thank Hassan Afrouzi, Jonas Arias, Borağan Aruoba, Guido Ascari, Susanto Basu, Christiane Baumeister, David Berger, Anmol Bhandari, Hilde Bjørnland, Fabio Canova, Yoosoon Chang, Olivier Coibion, Luca Gambetti, Domenico Giannone, Fabio Ghironi, Yuriy Gorodnichenko, Adam Gulan, Jonathan Heathcote, Ana María Herrera, Joseph G. Haubrich, Ayşe Ökten İmrohoroğlu, Barış Kaymak, Lutz Kilian, Ed Knotek, Jennifer La'O, Sarah Lein, Zheng Liu, Pierlauro Lopez, Junior Maih, Elmar Mertens, James Mitchell, Alessandro Melone, Brent Neiman, Juan Pablo Nicolini, Andrew Patton, Mathieu Pedemonte, George Pennacchi, Carolin Pflueger, Giorgia Piacentino, Giorgio Primiceri, Ivan Petrella, Vincenzo Quadrini, Robert Rich, Peter Ritchken, Ricardo Reis, Barbara Rossi, Juan Rubio-Ramírez, Eric Sims, Kjetil Storesletten, Allan Timmermann, Stephen Terry, Willem Van Zandweghe, Gustavo Ventura, Randal Verbrugge, Michael Weber, Toni M. Whited, Alexander Wolman, Michael Woodford, Cynthia Wu, Saeed Zaman, and Donghai Zhang for useful comments and suggestions. We thank Geena Panzitta for her excellent research assistance. The opinions expressed in this article are the sole responsibility of the authors and do not necessarily reflect the position of the Federal Reserve Bank of Cleveland or the Board of Governors of the Federal Reserve System.

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1 Introduction

One of the key functions that the Federal Reserve performs is to promote the stability of the US financial system. "The Federal Reserve's assessment of financial vulnerabilities informs decisions regarding the countercyclical capital buffer", a tool "designed to increase the resilience of large banking organizations ... and to promote a more sustainable supply of credit over the economic cycle".[1] The two key questions we want to answer in this paper are: should the Fed care about oil price fluctuations when deciding on how to set the countercyclical capital buffer? If so, is the countercyclical capital buffer policy effective in dealing with the consequences of oil price fluctuations? Those two questions are interesting because it is well documented that the Federal Reserve cares about oil price fluctuations when deciding how to set the federal funds rate, due to their effects on economic activity and inflation.[2] Therefore, it is worth investigating if that has to also be the case when the Fed decides on the capital buffer, due to the potential effects of those fluctuations on the US banking sector.

The first step is, then, to establish whether or not oil price fluctuations have a quantitative relevant impact on US banks and, as a result, could be a threat to financial stability. Indeed, the answer to our first key question critically depends on that. The micro-empirical evidence in this respect basically does not exist. Therefore, we use micro-level data on banks to study empirically the effect of oil price fluctuations on the balance sheets of US banks. We establish two stylized facts: 1) high oil prices have a negative impact on banks' balance sheets, and 2) the effect is more negative for banks with high leverage.

Then, the answer to our second key question is addressed within the context of a structural model. Therefore, we develop and estimate a dynamic stochastic general equilibrium (DSGE) model that rationalizes our new micro-level findings, in which we can convincingly evaluate the role of macroprudential policy in dealing with oil price fluctuations in the US, something never explored before in the literature. Our two stylized facts suggest that oil price movements affect banks' balance sheets pro-cyclically, with a stronger pro-cyclical effect for banks with higher leverage. This is in line with the financial accelerator theory, which postulates that pro-cyclical variations in intermediaries' balance sheets can be at the core of amplification mechanisms that intensify the effect of shocks, with stronger amplifications when leverage is higher (see Bernanke et al., 1999 and Gertler and Karadi, 2011). Hence, our empirical evidence gives a strong empirical foundation for the use of a model embedded with the financial accelerator mechanism.[3]

[1]See the Financial Stability Report of the Board of Governors of the Federal Reserve System. For the legal framework for the countercyclical capital buffer, see Regulation Q–Capital Adequacy of Bank Holding Companies, Savings and Loan Holding Companies, and State Member Banks, 12 C.F.R. pt. 217, app. A (2018). For recent policy discussions about the countercyclical capital buffer see the statements and the speeches by former Fed Governor Lael Brainard (Brainard, 2021, and Brainard, 2018a,b).

[2]See Gazzani et al. (2024) for a detailed description of a number of Federal Open Market Committee meetings in which participating members discussed oil price developments.

[3]Further support on that comes from the July 2022 Bank of England Financial Stability Report in which they argue that "commodity market disruption can affect the wider financial system, in particular through its impact on the broader macroeconomy and its potential to amplify macroeconomic shocks" (see Financial Policy Committee, 2022). And also from Castelnuovo et al. (2024) and Chan et al. (2024), as we explain later.

Our contribution is fourfold. First, we provide empirical evidence, based on panel regressions, of the effects of oil price fluctuations on banks' balance sheets, uncovering the new stylized facts described above. Second, through the DSGE model, we propose, characterize, and formalize the banks' balance-sheet transmission channel of oil price shocks. This provides a theoretical explanation for our empirical findings that banks' balance sheets are inversely related to oil price movements, and more so for highly leveraged banks. This also adds a brand new channel of transmission of oil price shocks to the long list of channels previously studied. Third, thanks to the estimation of the model, we evaluate that channel empirically and we test its relevance. Accordingly, we show that the effects of oil price shocks are amplified, making those shocks non-negligible drivers of the dynamics of US banks' intermediation activity and of the US real economy. Fourth, equipped with the appropriate model, we evaluate the effectiveness of a realistic countercyclical capital buffer policy responding to the evolution of banks' credit growth, modeled in a novel manner compared to the existing literature, to address oil price fluctuations. We show that such a policy is effective in mitigating the negative effects of high oil prices.

Our DSGE model includes a banking sector, mainly based on a framework of endogenously determined constraints on banks' balance sheets, as in Gertler and Karadi (2011), that accounts for the accelerator mechanism, and an oil sector as in Bjørnland et al. (2018). Like Bjørnland et al. (2018), we incorporate a direct channel of oil price shocks in assuming that oil enters the production function as an intermediate input. Our inclusion of the banking sector provides an indirect financial channel.[4] It is worth highlighting upfront that our mechanism is indirect as opposed to other mechanisms that are direct in nature. In particular, banks can for instance be directly exposed to oil price fluctuations in the following two circumstances: first, they can buy commodity derivatives, and second, they can extend loans to the US oil sector. In both cases, the oil price shock dynamics is completely opposite of the one we propose with our financial accelerator framework. In fact, an increase in the price of oil would be beneficial for banks' balance sheets in those two cases, and not detrimental, eventually generating a deceleration effect. However, we show within the model that both those channels are quantitatively marginal and, as a result, completely dominated by our accelerator mechanism if they are all present at the same time. Our stylized facts also confirm that finding by showing a negative impact of high oil prices on banks. Finally, we estimate our model with Bayesian techniques using real and financial US data as well as oil data for the period 1992Q1-2019Q4.

In more granular detail, the indirect financial channel we propose is supposed to amplify the effects of an oil price shock on the US economy, which initially hits 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 sheets 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. In fact, firms' borrowing costs are pushed up due to an increase in the credit spread. At the same time, the amount of credit in the economy decreases, forcing firms to cut investments even further. The result of all this is that the

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

economy suffers an even bigger contraction.

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. It is important to stress upfront that this is a result of our analysis and not something that is imposed by construction. In fact, the inclusion of the banking sector does not necessarily imply the existence of a statistically significant accelerator effect. Only the estimation can provide evidence in that respect.[5] Moreover, we show that the accelerator is not statistically significant for output if the impulse response functions are computed using draws from the prior distribution of the estimated parameters. This implies that data are key to getting our results.

The amplification mechanism has strong implications for the importance of oil price shocks. The variance decomposition 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).

Finally, given that we find that oil price shocks have a significant effect on borrowing and lending in the US banking sector and that this can amplify oil price shocks and generate large swings in the real economy, we introduce a countercyclical capital buffer policy to show how a realistic intervention could cope with that type of instability. We show that adjusting the buffer, within the regulatory limit of 2.5 percent, in response to the change in banks' credit growth caused by the change in the price of oil helps the US economy to be more insulated from oil price fluctuations. In particular, a reduction of the countercyclical capital buffer from 2.5 to 1.5 percent to counteract a large oil price shock, like the one that occurred in 2008Q2, reduces the volatility of the financial variables by about 50 percent and those of output and investment by 5-6 percent.

All 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). Moreover, the evaluation of macroprudential policy is only possible within our baseline model because in a model without banks there are no endogenous variables that the macroprudential authority could target.

Our results are robust to a handful of extensions, alternative model specifications, and issues such as the importance of oil supply shocks as opposed to oil demand shocks to explain the price of oil dynamics, the inclusion of shale oil, the fact that the US is now an important player in global oil production (but still a net importer of crude oil as of 2023), the relevance

[5] Moreover, it is well known that in DSGE models some shocks can lead to a deceleration effect instead, see, e.g., De Graeve (2008) and Gelain (2010).

of including nominal rigidities and monetary policy in the model, the exogeneity of oil prices with respect to the US economy, the time variation in the oil price shocks volatility, the inclusion of oil in consumption, the sample size, and the frequency of the data used.

The paper is structured as follows. In the next subsection, we review the relevant literature. Section 2 provides two stylized facts based on the panel regressions. Section 3 describes our baseline model and macroprudential policy. We then present the estimation details in Section 4, and our results in Section 5. Several robustness exercises are presented in Section 6. Finally, we offer some concluding remarks in Section 7.

1.1 Literature Review

We review two strands of the literature: 1) papers that somehow relate oil price fluctuations and banks, and 2) papers with DSGE models incorporating an oil sector.

Starting with banking, a very small group of papers corroborate our micro-evidence by providing macro-empirical evidence about the effects of oil price fluctuations on banks' activity. Gelain et al. (2024), in an SVAR setting à la Baumeister and Hamilton (2019), show that oil market shocks can have strong and long-lasting, or more modest and short-lived, effects on US banking variables depending on the source of the oil price fluctuations. Boufateh and Saadaoui (2021) analyze the response of bank loans to oil market shocks in a VAR à la Kilian (2009) and find that those shocks have significant effects. Qin (2020) provides evidence about the procyclicality of credit's response to oil market shocks. By introducing a systemic financial stress index in a VAR à la Kilian (2009), he finds that contractionary oil market shocks tend to increase systemic financial stress (and vice-versa).

Bidder et al. (2021) and Wang (2021) are two papers that use micro data. They are not strictly speaking "oil papers", but they still offer some useful insights. A clear indication that they are not "oil papers" is that they do not cite any paper by seminal scholars in this field. Bidder et al. (2021) and Wang (2021) both focus on the period 2014-2015 and they are interested in how banks, more or less exposed to the oil industry in the US, react to a negative net worth shock (in their case) generated by the large decline in the price of oil in that period. It is worth stressing that both papers, by focusing only on the period 2014-2015, might provide a set of results that are strictly related to that particular episode and that might not necessarily hold on average, or in other periods, if a longer sample such as ours with more oil episodes is considered. This is reminiscent of the results in Kilian (2008), according to which, "overall, exogenous oil supply shocks made remarkably little difference for the evolution of the U.S. economy since the 1970s, although they did matter for some historical episodes."

Bidder et al. (2021) 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. They show that the effect on total lending, total size of the balance sheet, and the degree of leverage appears to be ambiguous. Wang (2021) conducts a similar analysis, but focuses on regional banks. Both papers seem to suggest a mechanism that is the complete opposite of the one we propose. In fact, their evidence implies that low oil prices are bad news for banks. This apparent contradiction can be easily explained by the fact that these papers focus on those banks with significant exposure to the oil sector in the US in the period 2014-2016 and exploit granular banks data. Actually, the exposure was not large and did not pose any major problem to those banks and to the overall banking sector, as explained in 1) Baumeister and Kilian (2016) and 2) Garcia and Weber (2018), who, referring to the same period, conclude that "[d]uring the past few years, banks have exhibited flexibility in working with borrowers exposed to the [oil and gas] sector. Overall, only a small number of [Federal Deposit Insurance Corporation]-supervised banks exhibited supervisory concerns as a result of impacts from the oil price slide", and 3) some Moody's credit outlook reports commenting on the large decline in oil prices in the period 2014-2015 in which they conclude that "lower oil prices will broadly support bank creditworthiness [and they] are positive for the operating environment of US banks" (see Moody's, 2015b, Moody's, 2015c, and Moody's, 2015a).

Finally, 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 of 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.

As for the DSGE models, 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. A non-exhaustive list of these studies includes Kim and Loungani (1992), Rotemberg and Woodford (1996), Finn (2000), Leduc and Sill (2004), Carlstrom and Fuerst (2006), Bodenstein et al. (2008), Nakov and Pescatori (2010), Bodenstein et al. (2011), Bodenstein et al. (2012), Bodenstein et al. (2013), Balke and Brown (2018) and Bjørnland et al. (2018), Cakır Melek et al. (2021), Balke et al. (2024). From a theoretical point of view, our paper presents two major differences with respect to all of those papers: first those models do not include financial frictions of any sort, and second, as a result, there is no macroprudential analysis whatsoever.

2 Panel Regressions

In this section, we perform our empirical analysis based on panel regressions. The idea is to investigate whether oil price fluctuations have an impact on banks' net worth. If so, we also want to test if that impact depends on the degree of banks' leverage. This provides a direct test for the core feature of the financial accelerator theory. In the extreme case in which the leverage ratio is zero, we would be in a Modigliani-Miller world (see Miller and Modigliani, 1958), where banks' net worth position is irrelevant for the real economy. In the presence of a positive leverage, financial frictions matter and fluctuations in the net worth matter for the real economy. The higher the leverage is, the higher the risk involved in banks' activities, and the stronger the financial accelerator is.

We collect data on each constituent of the KBW Nasdaq bank index.[6] We follow Jones

[6]In the process of estimating the DSGE model, we use the Dow Jones US bank stock market index as

and Kaul (1996) for the specification of the main relationship we want to test. Moreover, we also incorporate the approach proposed in Borio et al. (2017), Kohlscheen et al. (2018), and Kim (2020), to include bank-specific and macroeconomic variables. Therefore, our panel specification indexed for bank i is:

$$\Delta n_{i,t} = \alpha + \sum_{s=0}^{4} \beta_s \Delta P_{o,t-s} + \gamma Lev_{i,t} + \delta_j X_t + b_i + \varepsilon_{i,t}$$

where $\Delta n_{i,t}$ is the quarter-on-quarter percent change in the real stock market index of each bank, α is a constant, $\Delta P_{o,t}$ is the quarter-on-quarter percent change in the real price of oil, $Lev_{i,t}$ is banks leverage, X_t is a vector of control macroeconomic variables, i.e., the quarter-on-quarter real US GDP growth rate, the inflation rate, and the federal funds rate, $j = GDP, \pi, ffr$, and b_i is banks' fixed effect. The estimation sample is 1992Q1-2019Q4. All data are described in detail in Appendix A.

Results of the panel regressions are in Table 1. For each estimation, we report the estimated coefficients, with the exception of the coefficients on the fixed effects. Following Jones and Kaul (1996), we primarily focus on the sum of the βs. Beside being the main approach of that paper, this seems appropriate in our context too because the price of oil in the DSGE model is modeled within a structural VAR model that contemplates some of its own lags. In column 1, we observe the results for all banks. We see that there is a negative effect of oil price fluctuations on banks' net worth. The sum of the βs is equal to -0.13. As highlighted by the F-statistics, this sum is statistically different from zero. The inverse relationship between oil price fluctuations and banks' balance sheets aligns very well with the anecdotal evidence emerging from a series of Moody's credit outlook reports commenting on the large decline in oil prices in the period 2014-2015 in which Moody's concludes that "lower oil prices will broadly support bank creditworthiness [and they] are positive for the operating environment of US banks" (see Moody's, 2015b, Moody's, 2015c, and Moody's, 2015a). Moreover, our findings are consistent with the macro-evidence on banks' net worth as in Gelain et al. (2024) and with the macro-evidence on the stock market as a whole (see Jones and Kaul, 1996, Kilian and Park, 2009, Aastveit, 2014, and Herrera and Rangaraju, 2020). Finally, Degiannakis et al. (2018) and Sadorsky (2019), in their comprehensive reviews, show that the vast majority of studies find a negative relationship between oil and the stock market.

Columns 2 and 3 report the results of the following thought experiment. We divide all banks into two groups: one group with banks whose leverage is higher than the average leverage across all banks, and one group with banks whose leverage is lower than the average leverage. The sum of the βs is again negative for both groups, but it is more negative for the group of banks with higher leverage: -0.28 versus -0.05 for the other group. The first group's sum is highly statistically significant, while the second group's not. That is a strong result that shows that only when banks are highly leveraged are they negatively affected by

a proxy for banks' net worth instead of the KBW Nasdaq bank index because the Dow is available for a slightly longer period. In this section, we use the latter because the list of its 24 constituents is publicly available, so we can collect data for each of them. On the contrary, for the Dow Jones US bank stock market index only the top 10 constituents are available. In aggregate, they are virtually identical. Therefore, it makes no difference which one is used to estimate the DSGE model.

oil price fluctuations, and they are not if they have low leverage. However, overall, the highly leveraged banks' effect seems to dominate, because the effect on all banks is negative and statistically significant. All the other parameters are basically not statistically significant, with a few exceptions for banks' leverage and the GDP growth rate. Those parameters have the right sign too. R^2s are all relatively low, but this is common in this type of panel regression (see Jones and Kaul, 1996).

We find a statistically significant impact of oil price fluctuations on banks' net worth. Is the impact also economically meaningful? Yes, because the cumulative effect of a 1 percent increase in the growth rate of the price of oil over five quarters is associated with a cumulative decline of 0.13 percent of banks' net worth growth rate over the five quarters for all banks and of 0.28 percent for highly leveraged banks, or, on average, 0.03 percent (all banks) and 0.06 percent (high leverage banks) each quarter. Looking at a specific episode, in the five quarters between 1999Q1 and 2001Q1, the growth rate of the price of oil increased 87 percent cumulatively. This translates into a remarkable cumulative drop of banks' net worth growth rate of 2.61 percent for all banks and 5.22 percent for banks with high leverage.[7]

Our panel regression analysis greatly confirms the idea that high oil prices have a negative impact on US banks. Moreover, it corroborates the hypothesis that highly leveraged banks suffer more from high oil prices, supporting the financial accelerator theory. All that can be thoroughly investigated in the context of our DSGE model.

3 Baseline Model

In this section, we describe our DSGE model, which embeds financial frictions in line with Gertler and Karadi (2011) in a real business cycle context.[8] As in Bjørnland 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.

3.1 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

[7]Those values are obtained as follows. The price of oil growth rate increased on average $87/5 = 17.4$ percent each quarter. Therefore, for all banks the net worth growth rate decreased $17.4*0.03 = 0.522$ percent per quarter, so $0.522*5 = 2.61$ percent cumulatively. For highly leveraged banks, the net worth growth rate decreased $17.4*0.06 = 1.044$ percent per quarter, so $1.044*5 = 5.22$ percent cumulatively.

[8]The main reasons why we opted for a real business cycle model are that 1) Bodenstein et al. (2012) show that "although oil intensity shocks ... explain much of the variation in the real price of oil since the mid-1980s ... these shocks explain little of the evolution of the U.S. federal funds rate. [Moreover], oil supply and foreign oil intensity shocks have had little impact on monetary policy in the United States", 2) Kilian and Lewis (2011) "document that there is no empirical support for an important role of monetary policy responses in amplifying the effects of oil price shocks", and 3) Bodenstein and Guerrieri (2012) find that "nominal rigidities and monetary policy are not important transmission channels for shocks that affect oil prices". We provide a version of our model with nominal rigidities in the robustness section.

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 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:

$$\max E_t \sum_{i=0}^{\infty} \beta^i \left[\ln \left(C_{t+i} - hC_{t+i-1} \right) - \frac{\chi}{1+\varphi} L_{t+i}^{1+\varphi} \right] \tag{1}$$

where : $0 < \beta < 1,\ 0 < h < 1, \varphi > 0$. 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 first-order conditions for labor supply and consumption are:

$$\Psi_t W_t = \chi L_t^{\varphi} \tag{3}$$

$$E_t \beta \Lambda_{t,t+1} R_{t+1} = 1 \tag{4}$$

with:

$$\Psi_t \equiv \left(C_t - hC_{t-1} \right)^{-1} - \beta h E_t \left[\left(C_{t+1} - hC_t \right)^{-1} \right]$$

$$\Lambda_{t,t+1} \equiv \frac{\Psi_{t+1}}{\Psi_t}$$

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

3.2 Financial Intermediaries

Financial intermediaries lend funds obtained from households to a non-financial final-goods-producing firm. 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:

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

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.[9] 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:

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

In the previous expression, we have that:

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

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

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

In equations (12) and (13), ν_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, $X_{t,t+i} \equiv Q_{t+i} S_{j,t+i} / Q_t S_{j,t}$, 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:

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

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

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

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:

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

Moreover, we have that:

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

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

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:

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

The total final period assets of exiting intermediaries at t are $(1-\theta_t) Q_t S_{t-1}$. 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:

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

3.3 Final-Goods-Producing Firms

Firms that produce final goods work in a perfectly competitive environment.[10] 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 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:

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

[10] 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.

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.[11] We assume that the depreciation rate is given by:

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

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:

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

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

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

where:

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

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:

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

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).

[11] 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".

3.4 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:

$$\max E_t \sum_{\tau=t}^{\infty} \beta^{T-t} \Lambda_{t,\tau} \left\{ \left(Q_\tau - 1\right) I_{n,\tau} - f\left(\tfrac{I_{n\tau}+I}{I_{n\tau-1}+I}\right)\left(I_{n,\tau}+I\right) \right\} \tag{34}$$

where $I_{n,t} = I_t - \delta\left(U_t\right)\xi_t K_t$, $f\left(1\right) = f'\left(1\right) = 0$ and $f''\left(1\right) > 0$, 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:

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

3.5 Oil Sector

We model the oil sector following Bjørnland et al. (2018). In our baseline model we do not consider, as they do, time-varying dimension and the multiplicity of regimes among which the economy can switch, but we do that in the robustness section. Following them, we assume that the price of oil is determined by a single sector located outside the US. This sector is modeled as a bi-variate structural VAR (SVAR) as follows:

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

where $\Delta \ln(GDP_t^W)$ denotes the growth rate of world GDP, and $P_{o,t}$ is the real oil price. The two innovations 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 advantages and limitations of this specification, which we totally share with Bjørnland et al. (2018), are discussed in the robustness section.

3.6 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 last term on the right-hand side captures the resources used for the adjustment costs in the production of new capital.

The government budget constraint is given by:

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

where government expenditure is financed by lump-sum taxes.

3.7 Macroprudential Policy

The way we set the countercyclical capital buffer policy is similar in spirit to the credit policy proposed in Gertler and Karadi (2011), but we develop it from a macroprudential policy perspective. This represents a novel contribution because macroprudential policy has never been modeled in this way in the literature.[12]

Specifically, there is a total banks' capital ratio in the economy, $1/\phi_{c,t}$, which is the sum of the private banks' capital ratio, $1/\phi_t$, and the regulatory capital ratio, $1/\phi_{r,t}$. The latter is set by the Fed as a proportion Φ of the total ratio:

$$\frac{1}{\phi_{r,t}} = \Phi\frac{1}{\phi_{c,t}} \tag{39}$$

The total capital ratio is:

$$\frac{1}{\phi_{c,t}} = \frac{1}{\phi_t} + \frac{1}{\phi_{r,t}} \tag{40}$$

Therefore, using equation (39):

$$\frac{1}{\phi_{c,t}} = \frac{1}{\phi_t} + \Phi\frac{1}{\phi_{c,t}} \tag{41}$$

Solving for $\frac{1}{\phi_{c,t}}$ gives:

$$\frac{1}{\phi_{c,t}} = \frac{1}{1-\Phi}\frac{1}{\phi_t} \tag{42}$$

[12]Other approaches used in the literature are: penalty functions penalizing deviations from the countercyclical capital buffer, e.g., Angelini et al. (2014), time-varying λ with endogenous response to credit variables, e.g., Pietrunti (2017), and tax/subsidy on banks' net worth set by the macroprudential authority, e.g., Gelain and Ilbas (2017) and Akinci and Queralto (2022).

The way the relevant equilibrium conditions are modified by the introduction of the macroprudential policy is reported in Appendix E.

The Fed sets the countercyclical capital buffer according to the following rule:

$$\frac{1}{\phi_{r,t}} = \frac{1}{\phi_r} + \kappa \left(CR_t^{gr} - CR^{gr} \right) \tag{43}$$

where CR_t^{gr} is the growth rate of credit to firms, i.e., $CR_t^{gr} = \ln(cr_t) - \ln(cr_{t-1}) + z_t$, $cr_t = CR_t/Z_t$, and $CR_t = Q_t K_t$. The choice of the credit growth is driven by the Basel III regulatory framework, which introduces a series of measures to achieve key objectives, among which "its primary objective is to use a buffer of capital to achieve the broader macroprudential goal of protecting the banking sector from periods of excess aggregate credit growth that have often been associated with the build-up of system-wide risk" (see Basel Committee on Banking Supervision, 2010).[13] Parameter κ regulates the intensity of the Fed's response to changing conditions in the credit market. We also assume that the parameter Φ can change over time to make equation (39) consistent with changes in $\frac{1}{\phi_{r,t}}$. See Appendix E for further details.

3.8 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:

$$\ln(\xi_t) = (1-\rho_\xi)\ln\xi + \rho_\xi \ln(\xi_{t-1}) + \sigma_\xi \varepsilon_t^\xi \tag{44}$$

$$\ln(G_t) = (1-\rho_g)\ln g + \rho_g \ln(G_{t-1}) + \sigma_g \varepsilon_t^g \tag{45}$$

$$\ln(\theta_t) = (1-\rho_\theta)\ln\theta + \rho_\theta \ln(\theta_{t-1}) + \sigma_\theta \varepsilon_t^\theta \tag{46}$$

$$\ln(\lambda_t) = (1-\rho_\lambda)\ln\lambda + \rho_\lambda \ln(\lambda_{t-1}) + \sigma_\lambda \varepsilon_t^\lambda \tag{47}$$

4 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.

4.1 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

[13]See also https://www.bis.org/bcbs/ccyb/index.htm.

growth, the growth rate of world GDP, and the real price of oil.[14] A detailed description of the data and their transformation is in Appendix A. We plot them in Figure A1. The measurement equations for those variables not pertaining to the oil sector are as follows:

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

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.

4.2 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.,

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

0.38, but it is the same as in Gelain and Ilbas (2017). 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.[15] 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.

Macroprudential Policy. These parameters are not used during the estimation, because the macroprudential analysis is conducted after that. This is legitimate, because the countercyclical capital buffer has always been kept to zero in the US. We set the steady state value of Φ to 10 percent to be consistent with the Basel Committee's recommendation of setting the countercyclical capital buffer at 2.5 percent. Therefore, we keep the total leverage ratio at 4, so that the total capital ratio, $\frac{1}{\phi_c}$, is equal to 25 and the steady state value of the regulatory ratio, $\frac{1}{\phi_r}$, is equal to 2.5 percent. We set the parameter κ to 0.5, which implies a reduction of 1 percentage point of the countercyclical capital buffer given the oil price shock that we simulate in our macroprudential policy analysis.

We report all the calibrated parameters in Table 2. The bottom part of that table presents the values of some quantities implied by steady state restrictions, as reported in Appendix C.

Priors of Estimated Parameters. Table 3 reports the priors of the parameters that are estimated with Bayesian techniques. The prior distribution for habit in consumption, h, 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.[16] 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.

5 Results

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

[15]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.

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

5.1 Oil Market Shocks Dynamics

We present the oil market dynamics in Figure 1. 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 Bjørnland et al. (2018).

In Figure 2 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 (see Table E1 in Appendix F.5), but we show robustness to other situations in which oil supply shocks can be equally important (e.g., Caldara et al., 2019 and Baumeister and Hamilton, 2019), or even more important than demand shocks (e.g., Känzig, 2021). 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). Alternatively, we could consider the solid blue line case as the outcome of shutting off the accelerator channel in our baseline model. We can show that this alternative strategy would lead to the same conclusions. We report the 5th and the 95th percentiles of the Bayesian impulse response functions distribution to evaluate them statistically.

The shock is basically the same for both models, because there is no feedback from the DSGE to the SVAR, as is the case in Bjørnland et al. (2018). Starting with the no-banking model, an increase in the price of oil 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 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 in the intermediaries' balance sheets in our baseline model and, because of the leverage constraint as in equation (19), a decrease in their net worth, consistent with our micro-evidence.[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 2, it is statistically significant for all

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

[18]The decrease in stock market measures following an oil price shock is also consistent with the macro-empirical evidence in Kilian and Park (2009), Aastveit (2014), Degiannakis et al. (2018), Sadorsky (2019), Herrera and Rangaraju (2020), and Gelain et al. (2024). Moreover, the effect of oil price shocks on banks' assets is consistent with the analysis in Moody's (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 in the credit spread following an oil price shock is consistent with the empirical evidence in Abbritti et al. (2020).

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.

The financial accelerator mechanism critically hinges on the plausibility of the size of the response of banks' net worth to the oil price shock. Is our response plausible? The short answer is: yes. First, the response is in line with our micro-evidence. In fact, we can compute the cumulative response of net worth growth to a 1 percent change in the growth rate of the price of oil in our model. This turns out to be -0.1, very close to the micro estimate of -0.13 for all banks.

Second, from a macro perspective it is not straightforward to validate quantitatively our results because there are no DSGE model references for our baseline model, since we are the first to estimate the effect of oil price shocks on the US banking sector. However, the empirical oil SVAR literature investigating the effects of oil price shocks on the stock market as a whole can offer some support. In particular, Kilian and Park (2009) find that an oil-specific demand shock that increases the price of oil by 14 percent leads to a decrease in their stock market index of about 3 percent. Our $5th$ and $95th$ percentiles of the impulse response functions show that the drop in banks' stock market index is between 3 and 4 percent for a shock of the same size. Our baseline estimation is quarterly, while Kilian and Park (2009)'s is monthly. One could average Kilian and Park (2009)'s response over the first three months and compare it with our response in the first quarter. Alternatively, we can rely on our monthly estimation in Appendix F.4, Figure E6, from which we see that, for the same shock size, net worth drops by a similar magnitude. Hence, everything is consistent.

To give a sense of the effect of the size of the accelerator on the real economy, we look at the response of GDP after 4 quarters from the moment an oil price shock that increases the price of oil by 10 percent has occurred. This comparison is not only in line with the oil SVAR literature's common practice, but it is also very convenient for us because the strongest acceleration effect happens exactly after 4 quarters. The response of GDP is 0.67, base on posterior modes. In the model without financial frictions the response is 0.5.

How does our baseline model GDP response relate to the literature? As already stressed, no structural models with financial frictions are available for a direct comparison. Hence, once again, we can rely on the oil SVAR literature. We are not seeking a validation of our 0.67, especially because there is no appropriate SVAR to relate to, but rather a confirmation that including some sort of financial dimension in the SVAR could signal the presence of an amplification mechanism in the data. In that respect, there are two papers that find a stronger response of US real economic activity when the financial side of the economy is included in the analysis. SVAR models without financial variables typically find a response of output to an oil price shock that increases the price of oil by 10 percent of about 0.15 percent or smaller after one year (see, for instance, Aastveit et al., 2015 and Caldara et al., 2019). On the contrary, Aastveit (2014) finds that US industrial production drops about 0.4 percent after one year, and even more subsequently, i.e., 1 percent after two years and 1.2 percent after three years, by considering an array of US financial variables in his FAVAR. Similarly, Castelnuovo et al. (2024) find a decrease in US industrial production of about 0.4 percent after one year by including a measure of the *global* financial cycle in their SVAR. They even conclude that "financial frictions cannot be ignored as a propagation mechanism of energy price shocks, particularly in the absence of a monetary policy response". Finally, it is worth mentioning a third paper, i.e., Chan et al. (2024). They calibrate a model for the euro area and show that financial frictions are important to characterize the response of real economic activity to energy shocks. In fact, in a two-agent New Keynesian model, they show that the existence of credit-constrained households implies that the economy experiences a deeper contraction after an increase in energy prices than in a representative household model where agents are not constrained.

It is also worth comparing our model *without* banking to previous works. The paper most comparable to ours is Bjørnland et al. (2018). They state that "following a standard deviation shock to oil price of approximately 15 percent, US GDP declines gradually, by 0.4-0.5 percent within two years". Our response under the same circumstances equals 0.78. This seems a bit on the high side if compared to Bjørnland et al. (2018). Do our results hinge on that? No, they do not. In fact, one might think that the response in our baseline model is so strong because the model in which we add the banking sector has a strong response to start with. Nevertheless, that is not the case and we can show that in two ways. First, in the next section we show that the relatively large response of GDP in the model without banking does not allow the oil price shock to play an important role in explaining fluctuations in the real economy. Second, in the robustness section, we show that introducing nominal rigidities makes the model without banking even closer to Bjørnland et al. (2018). Even in that context, the addition of financial frictions gives the same results as in our baseline analysis.

Finally, we would like to stress that the statistical significance of the accelerator mechanism is driven by the data, and not by prior distributions. In Figure 3 we show the impulse response functions calculated on the basis of 1000 draws from the prior distributions of the estimated parameters. Clearly, the statistical significance of the mechanism is not embedded in the priors, but rather it is the result of the estimation.

5.2 Variance Decomposition

In Table 4, 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 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). Moreover, our percentage aligns very well with the evidence in Bjørnland 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.[20]

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 of GDP growth, with its 20 percent or so explanatory power.[21] 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 shape the assets price dynamics. As a result, this shock does generate the right comovement 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 one-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 activity 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 market 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 market shock better than a model without that channel.

[20]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.

[21]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.

5.3 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 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 Bjørnland 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.

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.

The other period 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. In that period, 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. 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, and in most cases much smaller than that.[22] This is the reason why turbulence in the oil sector did not materialize on aggregate, as also stressed by Moody's (2015b), Moody's (2015c), and Moody's (2015a). This is also consistent with Garcia and Weber (2018), who, referring to the same period, conclude that "[d]uring the past few years, banks have exhibited flexibility in working with borrowers exposed to the [oil and gas] sector. Overall, only a small number of [Federal Deposit Insurance Corporation]-supervised banks exhibited supervisory concerns as a result of impacts from the oil price slide". We elaborate more on the distinction between banks exposed and not exposed to the oil sector in the robustness section.

Over the period 2014-2016, our banks' stock market index increased cumulatively by 15 percent, while our measure of the credit spread fall cumulatively by 4 percent. This strongly supports the mechanism in our model of falling oil prices pushing the stock market up and the spread down.

5.4 Macroprudential Policy Analysis

In this subsection, we describe our macroprudential analysis. We want to evaluate how effective a countercyclical capital buffer intervention is in order to cope with the negative consequences of an oil price shock. To be realistic, we engineer a shock to the price of oil whose magnitude is similar to the one observed in the data in a specific episode. In particular, we focus on the second quarter of 2008 when the price of oil deviated 90 percent from its mean value. We simulate our model as if only an oil price shock of such a magnitude occurred in the first period and we allow the effects to die out according to the endogenous model's dynamics. To judge the macroprudential policy, we simulate our baseline model, in which the parameter κ is equal to zero, and our counterfactual model in which the parameter κ is set to 0.5, such that the countercyclical capital buffer decreases by 1 percentage point, i.e., from 2.5 to 1.5 percent. We take the ratio of the standard deviations of the resulting simulated series of a set of endogenous variables.

In Table 5 we report the standard deviation ratios for output growth, investment growth, net worth growth, and credit growth. Macroprudential policy is very effective in stabilizing credit growth given that it is the variable it responds to, achieving a reduction in its volatility of more that 50 percent. Net worth is also well stabilized and less volatile by a factor of almost 50 percent. The real economy also benefits from a more stable financial sector. Both output growth and investment growth experience a reduction in volatility of about 5 percent each.

The mechanism that governs those results is as follows. The countercyclical capital buffer

[22]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.

is accumulated in good times and it is released in bad times. Since our simulation starts from the steady state, banks are already endowed with the 2.5 percent regulatory capital buffer and, once the buffer is reduced by the oil price shock, they restore it along the dynamics back to steady state. Having more net worth at their disposal when a negative shock hits the economy, banks are able to better absorb the negative consequences on their balance sheets. In other words, they still experience a reduction in their net worth, but at the end of the process, they are left with a larger net worth than in the case in which they did not have the extra capital buffer. As a result, they are less risky than otherwise, which implies that in response to the oil price shock the credit spread increases less, the amount of credit extended in the economy drops less, and the negative impact on the real economy is smaller. This works for all shocks, but we here quantify the effects only for the oil price shock.

6 Robustness

In this section, we run a series of robustness tests and we prove that all of our results are robust. Our exercises 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, the specification of the oil sector SVAR, the role of US home oil production, the effects of nominal rigidities and monetary policy, the switching nature of the oil price shock variance, the effects of oil price shocks on consumption, the endogeneity of the price of oil and the feedback effects from the rest of the world to the US economy. We report all figures, tables, and technical details in Appendix F.

Sample Size. Most of the empirical literature that analyzes oil price fluctuations considers data from the 1970s. Therefore, we extend our analysis to the period 1974q1-2019Q4. 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. The previous literature has not paid much attention to the stationarity of the oil price series.[23] 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 Bjørnland 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. The literature has studied the role of oil supply and oil demand in explaining oil price fluctuations. To summarize the debate at a very high level, Kilian (2009) argues in favor of oil demand. Kilian and Murphy (2012) and Kilian and Murphy (2014)

[23] 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).

confirm that. Recent contributions such as Baumeister and Peersman (2013), Baumeister and Hamilton (2019), Caldara et al. (2019), and Känzig (2021), among others, have found oil supply shocks to be more relevant than what Kilian originally found. Even more recently, Kilian (2022) reiterates that "... oil demand shocks are the dominant drivers of the real price of oil", and Kilian and Zhou (2023) 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". Our analysis is more in line with Kilian's findings both old and new. But since the debate is far from being settled, we want to prove that our results are robust to a setup in which oil supply shocks do not play a marginal role (our baseline model ignores them completely because even including them in the SVAR they would be completely irrelevant). Therefore, we extend our analysis by substituting our baseline SVAR with the specification provided by the most recent papers emphasizing the role of oil supply shocks, namely, Caldara et al. (2019) and Känzig (2021). In the interest of space, we refer the reader to the original papers for the details, but we also provide some details in the notes to tables and figures in Appendix F.5. For each model, we focus on the main drivers of the price of oil that each paper identifies as important (see Appendix F.5, Tables E2 and E4). For each alternative SVAR model, we keep the original sample and we re-estimate our model over that. This is a reasonable assumption because Caldara et al. (2019)'s and Känzig (2021)'s samples overlap well with our baseline and with our long sample robustness, respectively. Since the two alternative SVAR models are estimated with monthly data, we adopt the mixed-frequency approach as described in Appendix F.4. The main takeaways of this robustness are: 1) the financial accelerator is statistically significant for all relevant shocks in each alternative SVAR specification (Appendix F.5, Figures E7 and E8); 2) the importance of oil market shocks to explain real US GDP growth is always amplified in the model with banks along the lines of our baseline analysis (Appendix F.5, Tables E3 and E5).

US Home Oil Production (Shale Oil). There are two issues related to shale oil. The first relates to the exposure of US banks to the oil industry. The second is related to the impact that shale oil had on the US economy in general.

Addressing the first issue is equivalent to answering the following question: how crucial is the fact that the US is now one of the major oil producers in the world for the analysis of the transmission of oil price shocks via US bank balance sheets? The straight answer is: it is not crucial at all. The robustness "Oil Price Stationarity" alone shows that home oil production is not relevant for our results. In fact, our results hold if we estimate the model over the period 1992Q1-2004Q4, a period in which the US field production of crude oil was decreasing, going from 9.64 million barrels per day in 1992 to 8.30 million barrels per day in 2004. Oil production reached the minimum in 2008 with 7.78 million barrels per day, and then started skyrocketing afterward reaching 19.99 million barrels per day in 2022. Similarly, the share of US oil production with respect to global production decreased over the period 1992-2004, from roughly 12 percent to about 7.5 percent, testifying that the US was far from being a major oil producer in that period.[24] We can elaborate even further. From a theoretical point of view, the introduction in the model of home oil production would be straightforward. The extension of the banking sector would also be trivial. However, it

[24]Those shares refer to crude oil including lease condensate. Further details can be found on the U.S. Energy Information Administration website.

is equally trivial to show that all of that would not have any material impact on our results, especially in terms of the existence of the accelerator effect. It is sufficient to think how banks' balance sheets in equation (5) would be modified as follows:

$$\tau_o Q_t S_{j,t} + (1 - \tau_o) Q_t S_{j,t} = N_{j,t} + B_{j,t+1}$$

where $0 \leq \tau_o \leq 1$ is the share of loans to the US oil sector out of total loans. Understanding whether this extension is relevant or not for our results boils down to establishing the value for τ_o. Tiny values would imply that our financial accelerator effect would strongly dominate the financial decelerator effect coming from the presence of $\tau_o Q_t S_{j,t}$ on the balance sheet. Indeed, $\tau_o = 0$ delivers our baseline model. The data suggest that in our sample, on average, τ_o is a very small number, in the range of only 1-2 percent at best. For instance, in 2016, the ratio between outstanding debt to the oil and gas sector and total loans for the bank with by far the biggest ratio toward that sector, i.e., Morgan Stanley, was only 5 percent. See footnote 23 for further readings.

Turning to the second issue, even in this case, we can prove that the inclusion of shale oil is not relevant for our analysis. Our reading of the literature is that there is no consensus on whether shale oil had an impact on the price of oil and on the US economy so far. Some papers do not find any effect, while other papers find some effects. However, those effects are small, or they have been found to have materialized in the late 2010s, or even after 2020, and they are projected to be stronger in the future, or they refer to only some sectors of the economy, or they are positive during some years but negative during others, or they are not as big as the authors claim they are. All this supports our view that shale oil is not a necessary ingredient for our analysis. More in detail, Foroni and Stracca (2023), Balke and Brown (2018), Kilian (2016), Manescŭ and Nũno (2015) all find basically no effect. Shifting to those papers finding some effects, Kilian (2017), with his counterfactual, concludes that "the Brent price of oil would have been higher by as much as \$5 in 2009, but most of the cumulative effects of the fracking boom would have been observed between 2011 and mid-2014, with the counterfactual price exceeding the actual Brent price by as much as \$9 at times. Thereafter, the price differential becomes negligible again". Frondel and Hovarth (2019) seem to find a very large effect starting in the early 2010s. However, they admit that they overestimate the contribution of shale oil to the price of oil because they consider only supply factors. They state that "[t]he effect resulting from [our] simulation is quite high compared to the estimate of 10 dollars per barrel provided by Kilian (2017), which among other things is due to the fact that in our specifications the demand side is taken as given". Solarin (2020) shows that the contribution of shale oil to US GDP for the period 2002-2019 is, considering the period as a whole or sub-periods, at maximum as follows: a 1 percent increase in shale oil production leads to an increase of only 0.08 percent in US GDP. Gundersen (2020) claims that "U.S. supply shocks can account for up to 13% of the oil price variation over the 2003–2015 period". That refers, in the variance decomposition, to their contribution 18 months ahead. For the same period, US supply shocks count a more modest 2 and 1 percent at 1 and 6 months ahead horizons, respectively. Moreover, he shows that the average difference between the actual price of oil and his counterfactual without shale oil is way less than \$5 between 2013 and 2015, and zero before 2013. Cakır Melek et al. (2021) state that "the level of U.S. real GDP is 1.07 percent higher in 2015 than in 2010, accounting for about one tenth of actual economic growth over the same period", attributing that to shale production. However, if we read their results correctly, the cumulative contribution of shale oil to US GDP is negative for the period 2010–2020. Balke et al. (2024) show how the price of oil would have evolved in the absence of shale oil. Their results clearly show that shale oil had a somewhat meaningful impact on the price of oil only from 2019, included, onward. Bjørnland and Skretting (Forthcoming) document that after the shale boom, i.e., from 2012/2013 according to their dating, higher oil prices may no longer be unambiguously negative for the US economy because oil and non-oil nonresidential business investments pick up following an adverse oil-specific shock. At the same time, though, energy–intensive industries and aggregate consumption respond negatively as before. They conclude that "*[g]oing forward*, economic policy needs to take into account that the transmission of an oil-specific shock has changed with the shale oil boom and that there are heterogeneous effects across the US".[25]

Will US oil home production have a bigger impact on the price of oil in the future, as Balke et al. (2024) forecast? Will higher oil prices have unambiguous positive effects on the US economy, as the analysis in Bjørnland and Skretting (Forthcoming) seems to suggest? In that case, our model still offers a conceptual framework within which we can reason about the impact of oil price shocks and their quantification via the bank channel. It is easy to envision that the story would work in the opposite manner and the accelerator would work in the direction of amplifying the positive effects of higher oil prices. Of course, it will be possible to quantify the strength of that amplification only when those circumstances are realized and new data are available.

Nominal Rigidities and Monetary Policy. We have already emphasized that previous literature did not find monetary policy to be a key factor. However, more recent papers, e.g., Miyamoto et al. (2024), have challenged that literature by finding that systematic monetary policy is important for the transmission of oil shocks. Moreover, the interaction between nominal rigidities and financial frictions might play a role. This is the reason why we extend our baseline model to incorporate nominal rigidities and monetary policy. We call it New Keynesian baseline model. We decide to keep the real business cycle version as the baseline because it is way easier to convey the main intuitions in a simpler model. We report the estimated parameters in Table E6. As shown in Figure E10, the model dynamics is basically the same in terms of the variables in common with the baseline model. However, in the New Keynesian model, the increase in the price of oil puts upward pressure on the US inflation rate. The central bank reacts to that by increasing the federal funds rate. As shown in Figure E11, we still observe a quantitatively relevant amplification in the response of GDP to the oil price shock. This is visible also in the variance decomposition. Oil price shocks explain 1.87 percent, 3.21 percent, 3.21 percent, and 3.42 percent of GDP growth variability at horizons of 1, 4, and 16 quarters ahead, and infinity, respectively. In the New Keynesian baseline model, oil price shocks explain 7.72 percent, 11.33 percent, 11.83 percent, 12.06 percent of GDP growth variability at horizons of 1, 4, and 16 quarters ahead, and infinity, respectively. Those last four readings are very similar to the baseline ones. But in this context, the amplification is even stronger than in the baseline, since in the New Keynesian model without banking, oil price shocks count less than in its counterpart without nominal rigidities. If in the baseline we observe a response of GDP up to three times larger, here we

[25] Italics added.

see that response is up to more than four times larger.

Markov Switching. Following Bjørnland et al. (2018), we assume that there are two oil price volatility regimes: one in which volatility is high and one in which it is low.[26] This is done by assuming that the volatility of the oil price shock changes according to a Markov chain, i.e., $\sigma_{P_o}(S_t^{oil})$, where the Markov chain is given by:

$$S_t^{oil} \in \{\text{Low oil price volatility, High oil price volatility}\}$$

We estimate the transition probabilities from one regime to the other. We report them in Table E7. We also report the estimated values for σ_{P_o} in the two regimes. In Figure E12 we show the smoothed probabilities. As in Bjørnland et al. (2018), we identify three periods where the structural shocks to the oil price are in a high-volatility state in the sample part we have in common with them, i.e., 1992Q1-2014Q1. The first period (1998–2000) coincides with the East Asian crisis and the subsequent recovery. During this period the oil price first fell below $12, the lowest price since 1972, before it shot up again from 1999/2000. The spike in 2002–2003 coincides with the Venezuelan unrest and the second Persian Gulf war and is the second episode. The third episode, 2007–2008, coincides with what Hamilton (2013) calls a period of growing demand and stagnant supply. Since our sample ends in 2019Q4, we identify a fourth period of high volatility that Bjørnland et al. (2018) could not identify because their sample ends in 2014Q1. That is the period 2014-2016, a period in which the real price of oil declined by 67 percent.

In terms of the accelerator mechanism, we show in Figure E13 that the accelerator is present in both volatility regimes, but the implications for the relevance of the oil price shocks for the real economy are different. In fact, the variance decomposition shows that oil price shocks in the high regime explain 23 percent, 19 percent, 19 percent, 19 percent, and 8 percent, 9 percent, 9 percent, 10 percent of GDP growth volatility at horizons of 1, 4, and 16 quarters ahead, and infinity for the model with and without banking, respectively. In the low regime they explain 10 percent, 8 percent, 8 percent, 8 percent, and 3 percent, 4 percent, 4 percent, 4 percent, at horizons of 1, 4, 16 quarters ahead, and infinity for the model with and without banking, respectively

Oil and Household Consumption. It is reasonable to assume that shocks to the real price of oil can impact households as much as they impact firms. A higher price of oil would, for instance, increase for instance the price of gasoline. To account for that in our model, we could assume oil in the utility function. We did not do that for three reasons. First, our starting point in terms of modeling is Bjørnland et al. (2018). They also do not include oil on the household side. Second, if anything, adding oil in the utility function would reinforce our results. A higher price of oil would have a negative impact on consumption. Firms would see reduced the demand for their goods, so they would cut production. The resulting reduction in production would add up to the reduction coming from the higher cost of the oil input. Therefore, GDP would fall more than in our baseline analysis. This would generate a bigger fall in investments, capital demand, price of capital, banks' net worth, and credit

[26] They also assume a high macroeconomic volatility regime as opposed to a low one, and two regimes for monetary policy, i.e., dovish and hawkish. The latter cannot be accounted for in our baseline specification. We abstract from the macroeconomic volatility in the interest of space. Moreover, it is worth highlighting that we could improve over their analysis because we could also define two financial volatility regimes.

and a larger increase in the credit spread. Third, since we focus on financial frictions, once oil is introduced on the household side, it would also be natural to assume that households borrow and face some sort of financial frictions. Adding those frictions would introduce another accelerator effect, reinforcing our results even further. But that would come at the cost of making the model unnecessarily complicated. The recent evidence in Chan et al. (2024) corroborates all our conjectures.

Price of Oil's Endogeneity and Feedback Effects from the Rest of the World to the US Economy. The specification of the oil SVAR follows Bjørnland et al. (2018). Therefore, we share with them all its advantages and limitations. There are two issues that they ignore completely that are worth discussing: first, the price of oil's endogeneity, i.e., the feedback effects from the US economy to the price of oil, and, second, the feedback effects from the rest of the world to the US economy. Starting with the former, one might be tempted to argue that we missed the effects from the US to the price of oil. This is erroneous for different reasons. First, if it is true that any of the US shocks directly move the price of oil in our baseline model, it is also true that the way the SVAR in (36) is specified already takes into account the effect of US GDP on the price of oil. In fact, world GDP in the SVAR includes US GDP. Second, even in models in which the price of oil is strictly endogenous, i.e., Bodenstein and Guerrieri (2012) and Bodenstein et al. (2012), US shocks count basically as nothing in explaining it. Foreign shocks explain 95 percent of it. Third, our analysis is the same as the one in Kilian (2009) who first estimates his oil market SVAR and then regresses the residuals from the SVAR on US GDP and on the US inflation rate.[27] The difference is that he does that in a two-step procedure, while we do it in a single step within the same model. Finally, if all of that evidence is not convincing enough, we add the following exercise: we add the US GDP growth as an extra variable in the equation of the price of oil in the SVAR. We assign a parameter to that variable and we re-estimate the model including that parameter among the estimated ones. As Figure E14 and Table E8 show, our results are unaffected, testifying that all the relevant feedback effects from the US to the price of oil are already taken into account in our baseline model. Turning to the feedback effects from the rest of the world to the US economy, there is indeed one potential issue: in our model, world GDP affects the US economy only through its effects on the price of oil, via its lags in the SVAR in (36). Hence, we miss the direct effect. For that reason, we perform the following exercise: we allow the world economic activity shock to directly affect the US economy. We do that by allowing a direct effect of the global real economic activity shock in the SVAR in (36) on all US shocks according to the specification in Appendix F.9, where further details can be found. As Figure E15 shows, we now observe a bigger, but still on average minor, role of the global real economic activity shock in explaining US GDP growth than in our baseline analysis, which is very much in line with the finding in Bodenstein and Guerrieri (2012) and Bodenstein et al. (2012) who also find that foreign shocks are very unimportant drivers of US GDP. However, this does not alter our results in terms of the importance of oil price shocks, especially during the Great Recession.

[27] Recently, Herrera and Rangaraju (2020) adopted a similar approach to re-evaluate the effects of oil supply shocks on US economic activity.

7 Conclusions

In this paper, we investigate whether or not it is relevant for the Federal Reserve to account for oil price fluctuations when deciding about the countercyclical capital buffer, one of the main tools to preserve financial stability. And if it is relevant, how effective could an intervention be. The answer to this first issue depends critically on whether or not oil price fluctuations can be a threat to financial stability by having quantitatively relevant effects on the US banking sector.

The micro-evidence in that respect is basically non-existent. That is why we first consider US micro-level data on banks, why we run panel regressions, and why we establish two stylized facts: 1) high oil prices have a negative impact on banks' balance sheets, and 2) the effect is more negative for banks with high leverage.

The evaluation of macroprudential policy is conducted within the context of a structural model. Our two stylized facts are consistent with the financial accelerator theory (see Bernanke et al., 1999). Therefore, we build and estimate a dynamic stochastic general equilibrium model embedded with such a mechanism with a banking sector, as in Gertler and Karadi (2011), and an oil sector as in Bjørnland et al. (2018).

We show that the model provides useful insights into how relevant oil price shocks are to explain the baking sector and the real US economy dynamics. 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. We also show that our model is quantitatively in line with our micro-evidence and with the relevant oil literature.

Having a realistic model that rationalizes the micro-empirical evidence and quantifies a relevant effect of oil price fluctuations on the US banking sector and on the US real economy allows us to convincingly evaluate the effects of macroprudential policy. We show that adjusting the buffer, within the regulatory limit of 2.5 percent, in response to the change in banks' credit growth caused by the change in the price of oil helps the US economy to be more insulated from oil price fluctuations. In particular, a reduction of 1 percentage point in the buffer, from 2.5 to 1.5 percent, to counteract a large oil price shock, such as the one that occurred in 2008Q2, reduces the volatility of the financial variables by about 50 percent and those of output and investment by 5-6 percent.

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Tables and Figures

Table 1: **Panel regression results**

$\Delta n_{i,t} = \alpha + \sum_{s=0}^{4} \beta_s \Delta P_{o,t-s} + \gamma Lev_{i,t} + \delta_j X_t + b_i + \varepsilon_{i,t}$			
$\sum_{s=0}^{4} \beta_s$	-0.13	-0.28	-0.05
α	1.73	-3.29	0.10
	(0.48)	(-1.02)	(0.03)
γ	-0.30*	-0.41*	-0.22
	(-2.04)	(-2.30)	(-0.76)
δ_{GDP}	6.28***	6.30***	6.22***
	(6.89)	(3.89)	(5.79)
δ_{π}	2.15	6.52	-0.15
	(1.02)	(1.62)	(-0.06)
δ_{ffr}	0.84	2.76*	0.01
	(1.26)	(2.00)	(0.01)
Number of obs.	2356	826	1530
Number of banks	24	9	15
R^2	0.09	0.10	0.09
F-statistics $H : \sum_{s=0}^{4} \beta_s = 0$	3.71**	5.26**	0.34
H p-value	0.05	0.02	0.56

Notes: The table reports the results from the panel regressions. Column 1 refers to all banks, column two to the group of banks with leverage above average, and column three to the group of banks with leverage below average. t-statistics are reported in parenthesis. ***, **, and * indicate statistical significance at 1 percent, 5 percent, and 10 percent, respectively. All coefficients of banks' fixed effects are not reported in the table in the interest of space.

Table 2: **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
SS Regulatory Capital Ratio Over Total Capital Ratio*	Φ	–	–	0.1	0.1
SS Countercyclical Capital Buffer*	$\frac{1}{\phi_r}$	–	–	0.025	0.025
Fed's Response to Credit Conditions*	κ	–	–	0.5	0.5
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). *Receives a positive value only in the counterfactual model where macroprudential policy is active.

Table 3: **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). In the interest of space the $5th$ and $95th$ percentiles are not reported. They are available upon request.

Table 4: **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

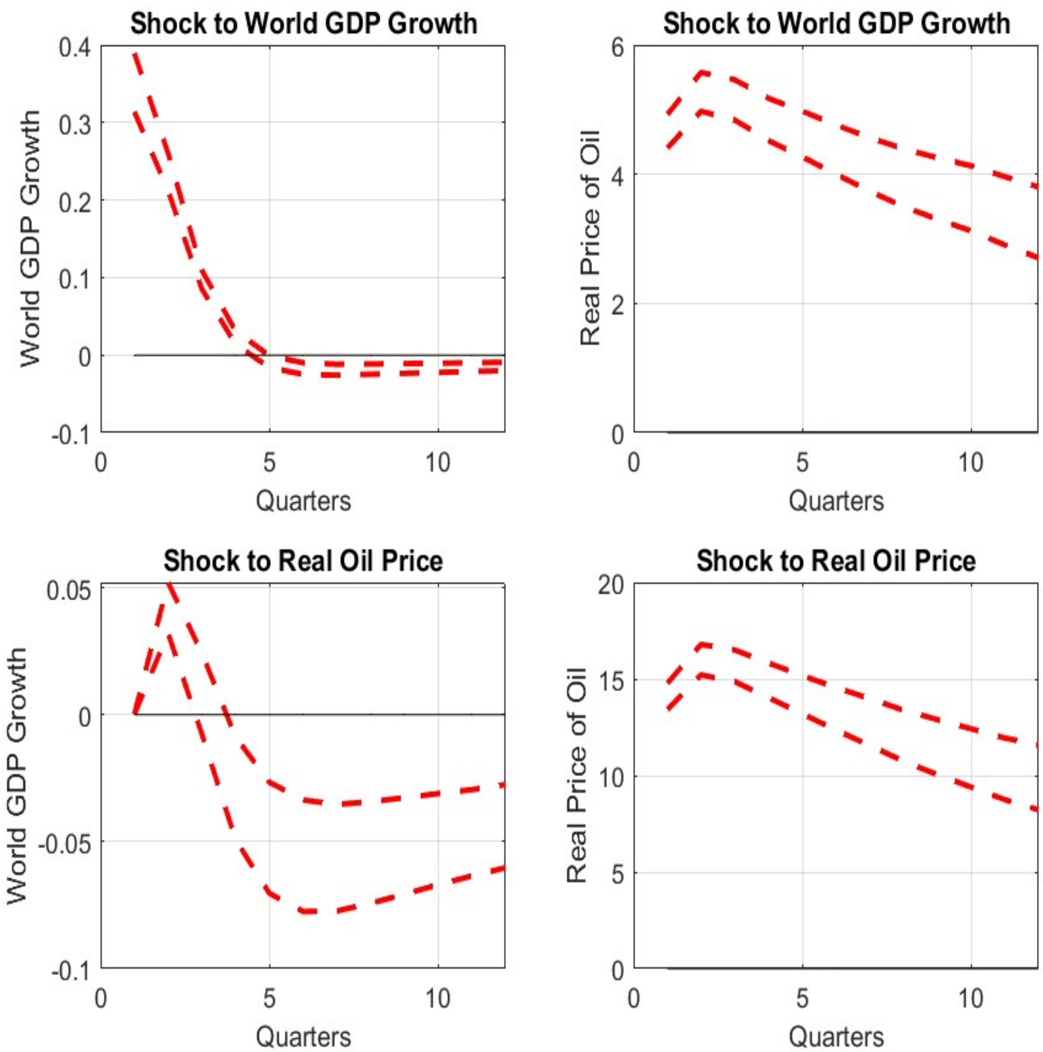
Notes: The table shows the real per capita GDP growth variance decomposition for different horizons and different model specifications: RBC model (first column), RBC model plus the oil sector (second column), RBC model plus the banking sector (third column), and our baseline model with both the oil and the banking sectors (fourth column). The variance decomposition is computed at the posterior modes. We also computed the variance decomposition by taking 1000 draws from the posterior distributions, such that we generate a distribution of 1000 variance decompositions. The $50th$ percentile of that distribution gives the same values reported in this table. Moreover, the distribution can be used to calculate the $5th$ and the $95th$ percentiles and to show that all decompositions are statistically different. In the interest of the table's readability we do not report them. They are available upon request.

Table 5: **Macroprudential Policy**

Variable	Ratio between standard deviations of variables with and without macroprudential policy
Output growth	0.95
Investment growth	0.94
Net worth growth	0.52
Credit growth	0.47

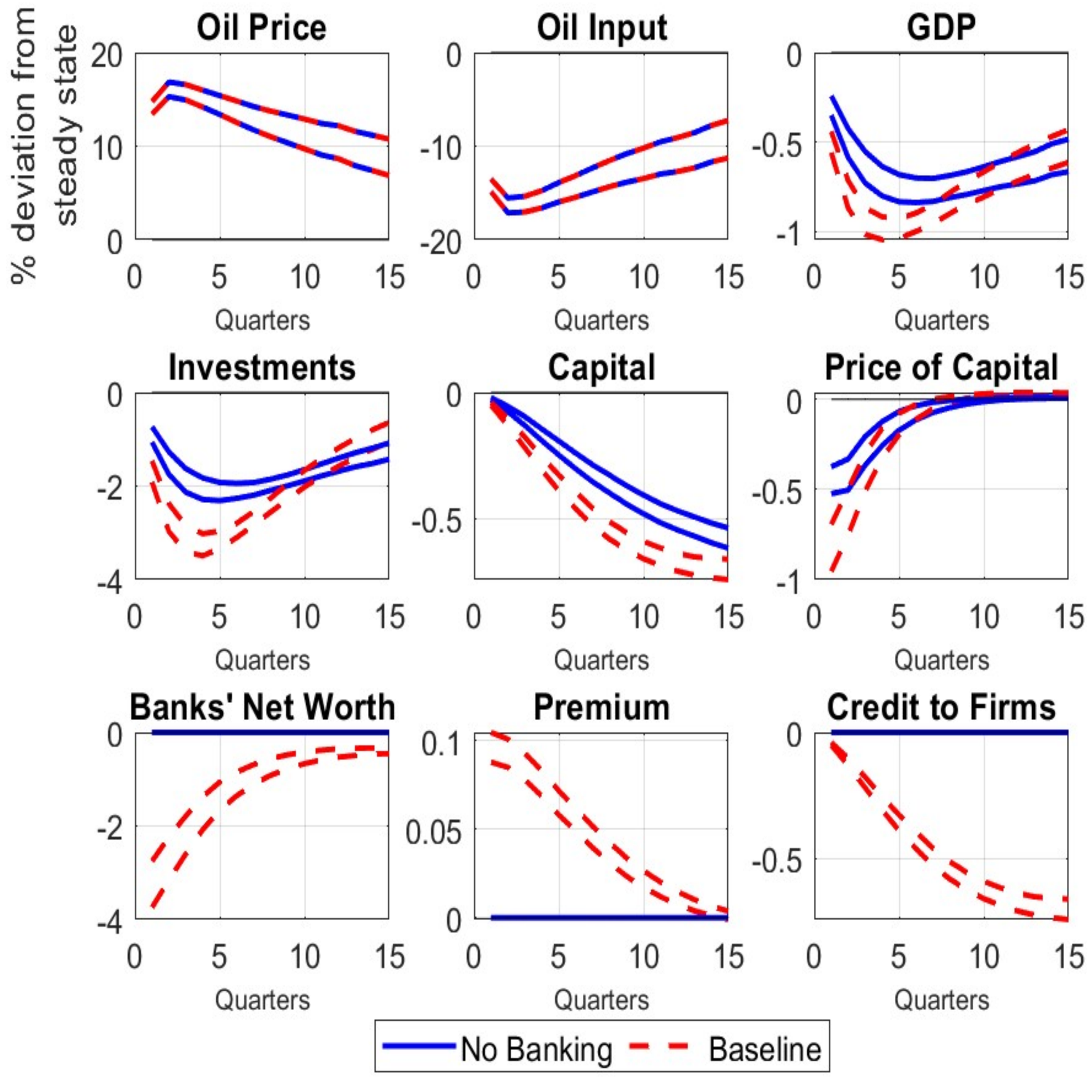
Notes: The table shows the ratios between the standard deviations of the variables simulated in the baseline model with macroprudential policy ($\kappa = 0.5$) and in the model without macroprudential policy ($\kappa = 0$), respectively, given an oil price shock that increases the price of oil by 90 percent. The countercyclical capital buffer is reduced from 2.5 to 1.5 percent. A ratio smaller than one means that the implementation of the macroprudential policy reduces the volatility of the variable by x percent, where $x = (1 - ratio)100$.

Figure 1: **Oil sector dynamics**



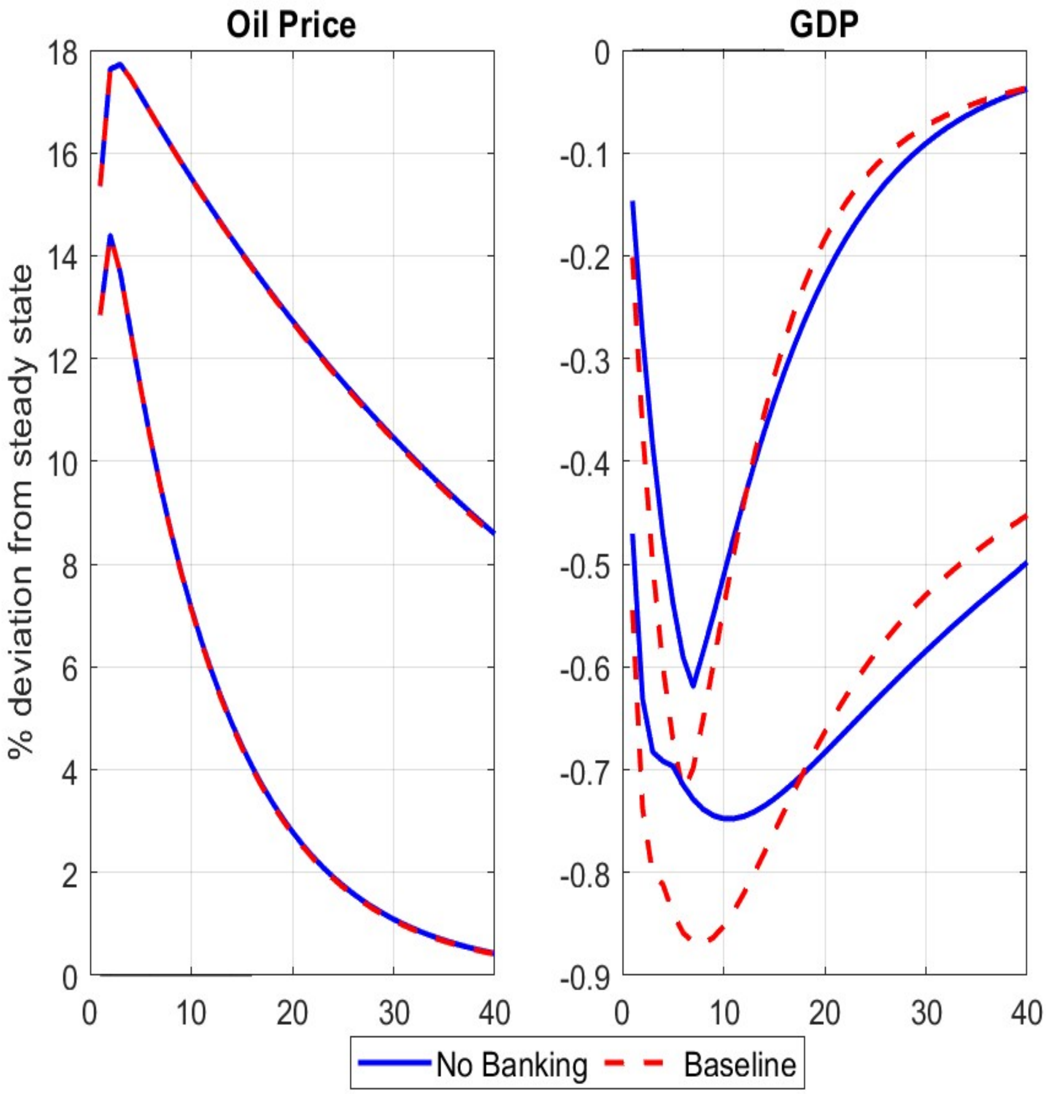
Notes: The figure shows the impulse response functions of the growth rate of world GDP and of the real price of oil to an estimated one standard deviation shock to world GDP growth and to the real price of oil, respectively. The graphs report the $5th$ and $95th$ percentiles of the responses' distribution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

Figure 2: **Oil price shock dynamics**



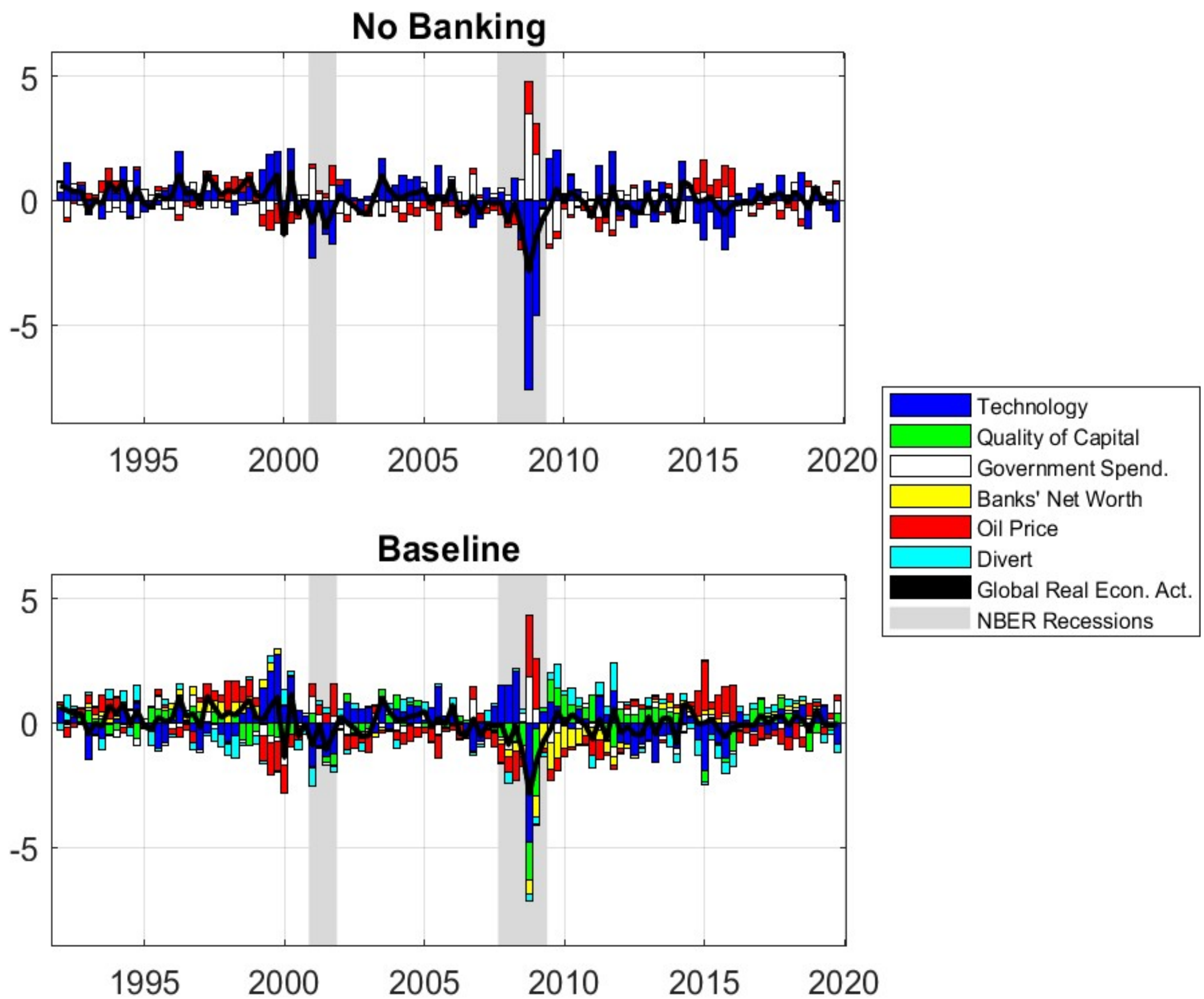
Notes: The figure shows the impulse response functions of the key variables to an estimated one standard deviation shock to the real oil price. The graphs report the 5*th* and 95*th* percentiles of the responses' distribution for each variable. The solid blue lines indicate an RBC model with oil only,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

Figure 3: **Oil price shock dynamics based on prior means**



Notes: The figure shows the impulse response functions of the price of oil and output to an oil price shock based on 1000 draws from the prior distributions of the estimated parameters. The graphs report the $5th$ and $95th$ percentiles of the responses' distribution 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.

Appendices - All the material from this point onward is for an online Appendix

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:

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

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.

As for 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).

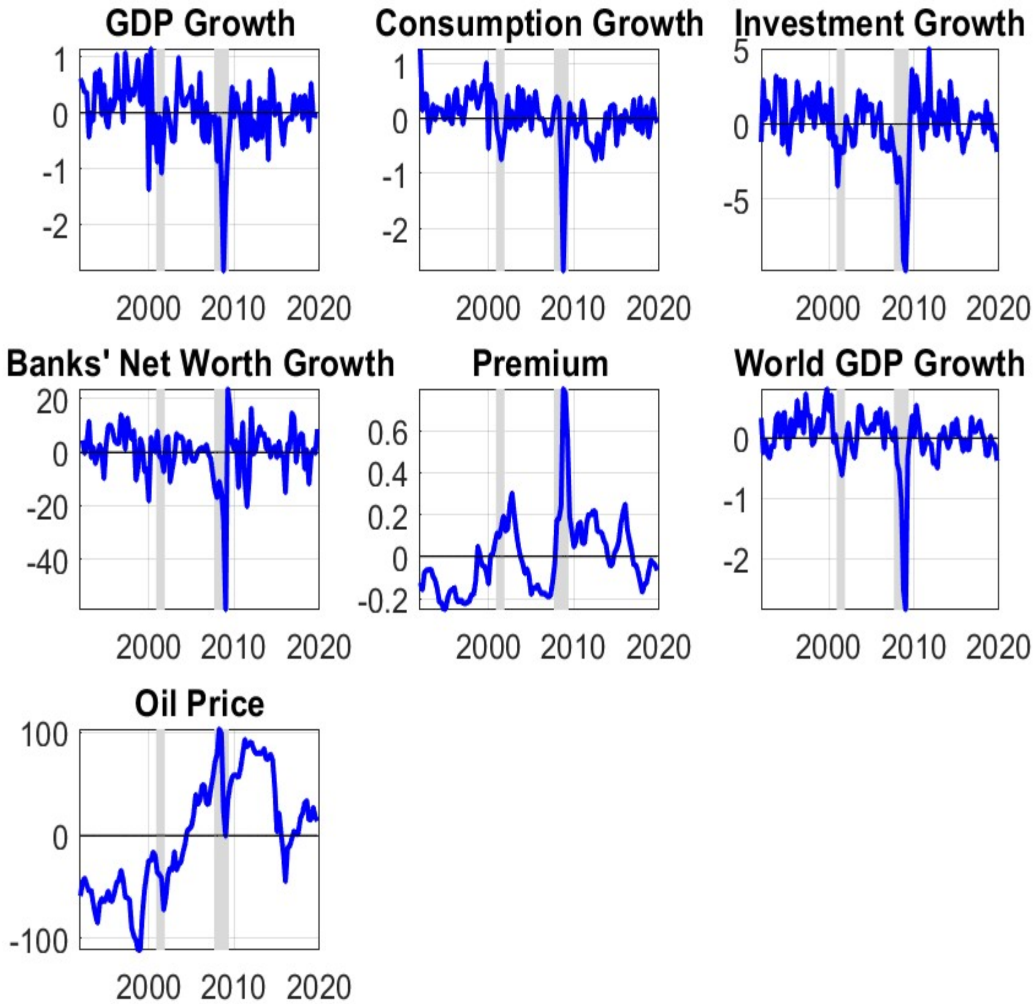
In the robustness to nominal rigidities we use the quarter average federal funds rate [DFF], downloaded from https://fred.stlouisfed.org/series/DFF, the quarterly Personal Consumption Expenditures: Chain-type Price Index [PCEPI], downloaded at https://fred.stlouisfed.org/series/PCEPI, the average quarterly hours of production and nonsupervisory employees for total private industries [AWHNONAG], downloaded at https://fred.stlouisfed.org/series/AWHNONAG, and the quarterly compensation per hour for the non-farm business sector [COMPNFB], downloaded at https://fred.stlouisfed.org/series/COMPNFB. Those variables are transformed as follows:

$$
\begin{aligned}
\text{Federal funds rate} &= (1/4) * (DFF) \\
\text{Inflation} &= 100\Delta LN(PCEPI) \\
\text{Hours worked} &= 100LN((AWHNONAG * CE16OV/100)/LNSINDEX) \\
\text{Real wage growth} &= 100\Delta LN(COMPNFB/GDPDEF)
\end{aligned}
$$

where [CE16OV] is the employment level, downloaded at https://fred.stlouisfed.org/series/CE16OV.

Finally the data for the panel regressions. The total assets figure and total liabilities figure are retrieved from Compustat – Capital IQ's Fundamentals Quarterly database on the WRDS platform using the mnemonics "ATQ" and "LTQ." The database uses the total value of assets and the total value of liabilities as reported on the firms' balance sheets in their 10-K and 10-Q filings. The total value of assets is defined as the sum of current assets; net property, plant, and equipment; intangible assets; investments and advances; and other non-current assets. The total value of liabilities is defined as the sum of current liabilities, long-term debt, deferred taxes and investment tax credit, and other non-current liabilities. Note: the total liabilities figure in the database is missing for First Republic Bank ("FRCB") for quarters 1, 2, and 3 of 1993; for these quarters, total liabilities is calculated as the difference between total assets and total stockholders' equity ("SEQQ."). The total stockholders' equity figure is calculated as the difference between total assets and total liabilities. The leverage figure is calculated as the ratio of total assets to total stockholders' equity. The quarterly stock price figure represents the unadjusted close price for the fiscal quarter end date. It is retrieved from Compustat – Capital IQ's Fundamentals Quarterly database on the WRDS platform using the mnemonic "PRCCQ." The adjusted stock price figure represents the close price for the fiscal quarter end date adjusted for stock splits and stock dividends. It is calculated as the unadjusted stock price divided by the cumulative adjustment factor ("AJEXQ."). The real adjusted stock market index is calculated as the adjusted stock price divided by PCE.

Figure A1: **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.

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:

$$\psi_t = \left[\left(c_t - h\frac{c_{t-1}}{e^{z_t}}\right)\right]^{-1} - \beta h\left[(c_{t+1}e^{z_{t+1}} - hc_t)\right]^{-1} \tag{48}$$

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:

$$\chi L_t^{\varphi} = \psi_t \varrho \alpha \frac{y_t}{L_t} \tag{49}$$

The value of banks' capital is given by:

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

The value of banks' net worth 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:

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

The growth rate of banks' capital is given by:

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

The growth rate of banks' net worth 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:

$$y_t = L_t^{\alpha} \left[\omega_k \left(U_t \xi_t k_t \right)^{1-\varrho} + \left(1 - \omega_k \right) o_{y,t}^{1-\varrho} \right]^{\frac{1-\alpha}{1-\varrho}} \tag{50}$$

The FOC for U_t is given by:

$$\left(1 - \alpha \right) \omega_k \frac{y_t}{U_t^{\varrho}} \left(\frac{\xi_t k_t}{a_t} \right)^{1-\varrho} = b U_t^{\zeta} \xi_t k_t \tag{51}$$

where:

$$a_t = \left[\omega_k \left(U_t \xi_t k_t \right)^{1-\varrho} + \left(1 - \omega_k \right) o_{y,t}^{1-\varrho} \right]^{\frac{1}{1-\varrho}} \tag{52}$$

The FOC for W_t:

$$w_t = \alpha \frac{y_t}{L_t} \tag{53}$$

The return to capital:

$$R_{k,t+1} = \frac{\xi_{t+1} \left[\left(1 - \alpha \right) \omega_k \frac{y_{t+1}}{\xi_{t+1} \left(e^{z_{t+1}} k_{t+1} \right)^{\varrho}} \left(\frac{U_{t+1} \xi_{t+1}}{e^{z_{t+1}} a_{t+1}} \right)^{1-\varrho} + Q_{t+1} - \delta \left(U_{t+1} \right) \right]}{Q_t} \tag{54}$$

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

$$P_{o,t} = \left(1 - \alpha \right) \left(1 - \omega_k \right) \frac{y_t}{o_{y,t}^{\varrho}} \frac{1}{\left(a_t \right)^{1-\varrho}} \tag{55}$$

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:

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

The net investment is given by:

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

The capital accumulation equation is given by:

$$k_{t+1}e^{z_{t+1}} = \xi_t k_t + i_{n,t} \tag{56}$$

The aggregate resource constraint is given by:

$$y_t = P_{o,t}o_{y,t} + c_t + i_t + G_t + \frac{\eta_i}{2}\left(\frac{i_{n,t}+i}{\frac{i_{n,t-1}}{e^{z_t}}+i} - e^z\right)^2 (i_{n,t}+i) \tag{57}$$

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-goods-producing firms' FOCs:

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

Assuming $L = 1/3$, we solve numerically and simultaneously equations (48), (49), (50), (51), (52), (53), (54), (55), (56), and (57), 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:

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

$$x = f e^z$$

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

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

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

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

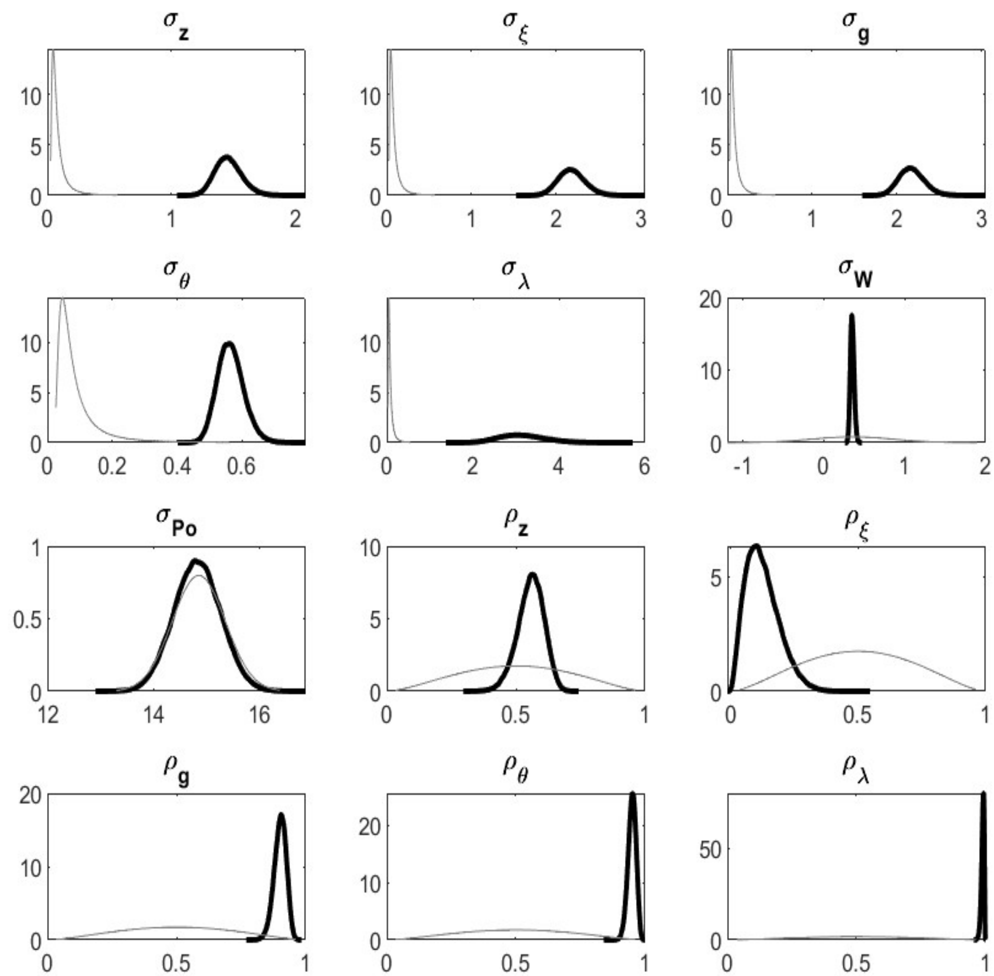
$$n = \frac{k}{\phi}$$

$$n_e = \theta f N$$

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

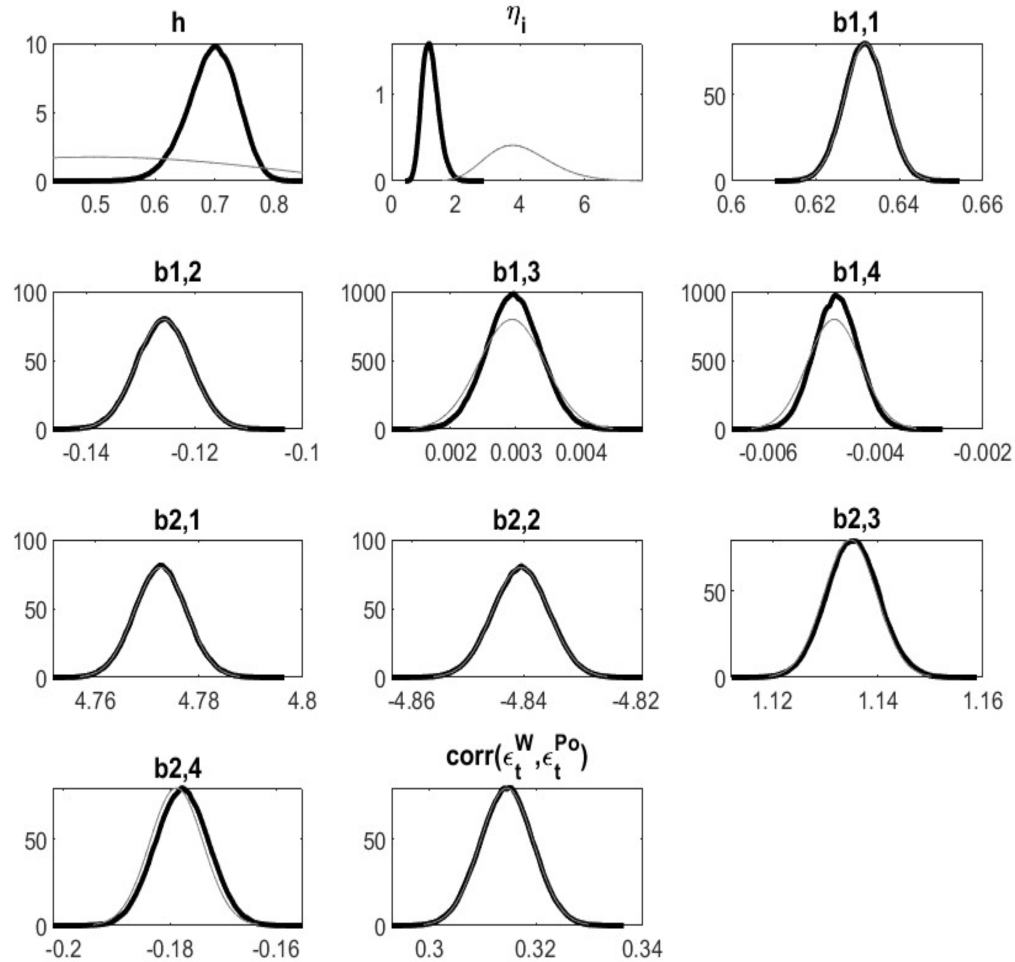
D Prior and Posterior Distributions

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



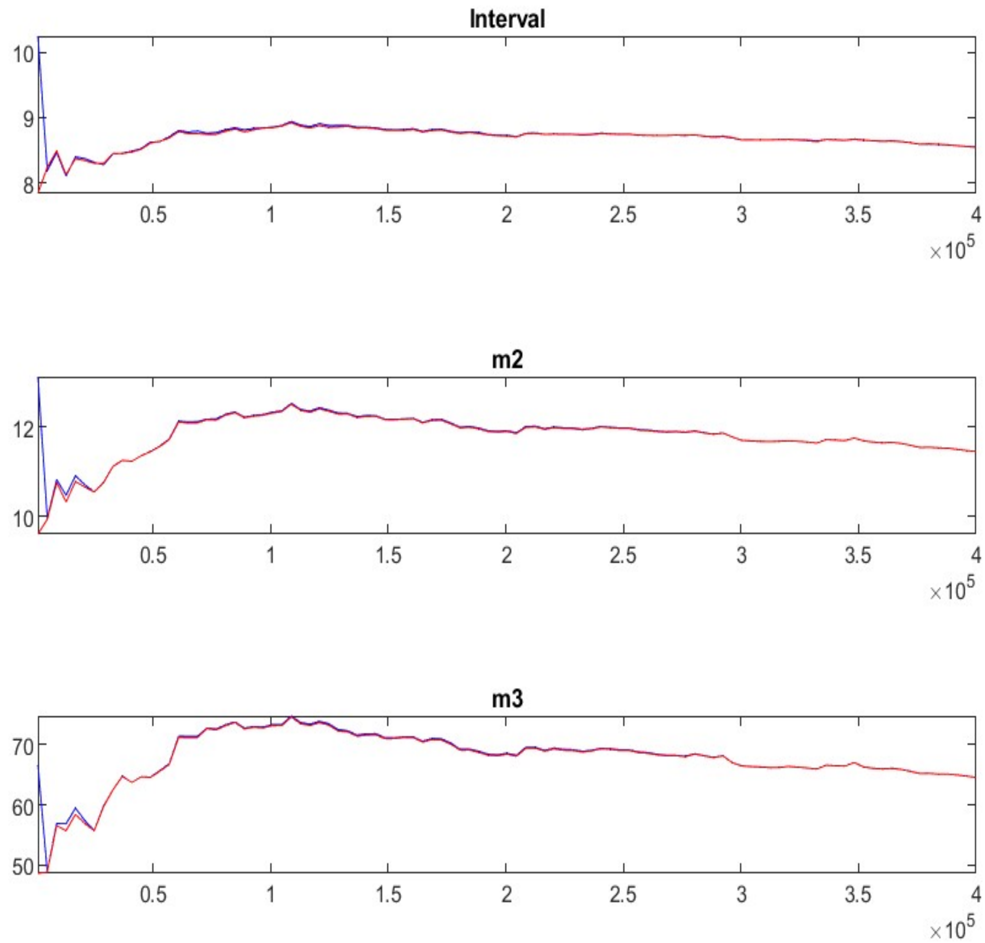
Notes: In the graphs above, the thin gray lines represent the prior distributions and the thick dark lines correspond to the posterior distributions.

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 Macroprudential Policy

In this Appendix we show which equilibrium conditions are affected by the introduction of the macroprudential policy.

The optimal leverage is given by:

$$\phi_{c,t} = (1 - \Phi_t) \underbrace{\frac{\eta_t}{\lambda_t - \nu_t}}_{\text{Private Leverage}}$$

The value of banks' capital is given by:

$$\nu_t = E_t \left\{ (1 - \theta_t)\, \beta \frac{\psi_{t+1}}{\psi_t e^{z_{t+1}}} \left(R_{kt+1} - R_{t+1} \right) + \beta \frac{\psi_{t+1}}{\psi_t} \theta_{t+1} \frac{\frac{\phi_{c,t+1}}{1-\Phi_{t+1}}}{\frac{\phi_{c,t}}{1-\Phi t}} f_{t,t+1} \nu_{t+1} \right\}$$

The growth rate of banks' capital is given by:

$$f_{t,t+1} e^{z_{t+1}} = \left(R_{k,t+1} - R_{t+1} \right) \frac{\phi_{c,t}}{1 - \Phi_t} + R_{t+1}$$

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

$$X_{t,t+1} = \frac{\frac{\phi_{c,t+1}}{1-\Phi_{t+1}}}{\frac{\phi_{c,t}}{1-\Phi_t}} f_{t,t+1} e^{z_{t+1}}$$

New banks' net worth is given by:

$$n_{n,t} = \frac{\omega}{1 - \Phi_t} Q_t \xi_t k_t$$

The regulatory capital ratio is given by:

$$\frac{1}{\phi_{r,t}} = \frac{1}{\phi_r} + \kappa \left(CR_t^{gr} - CR^{gr} \right) \tag{58}$$

The variable Φ_t is determined by the following equation:

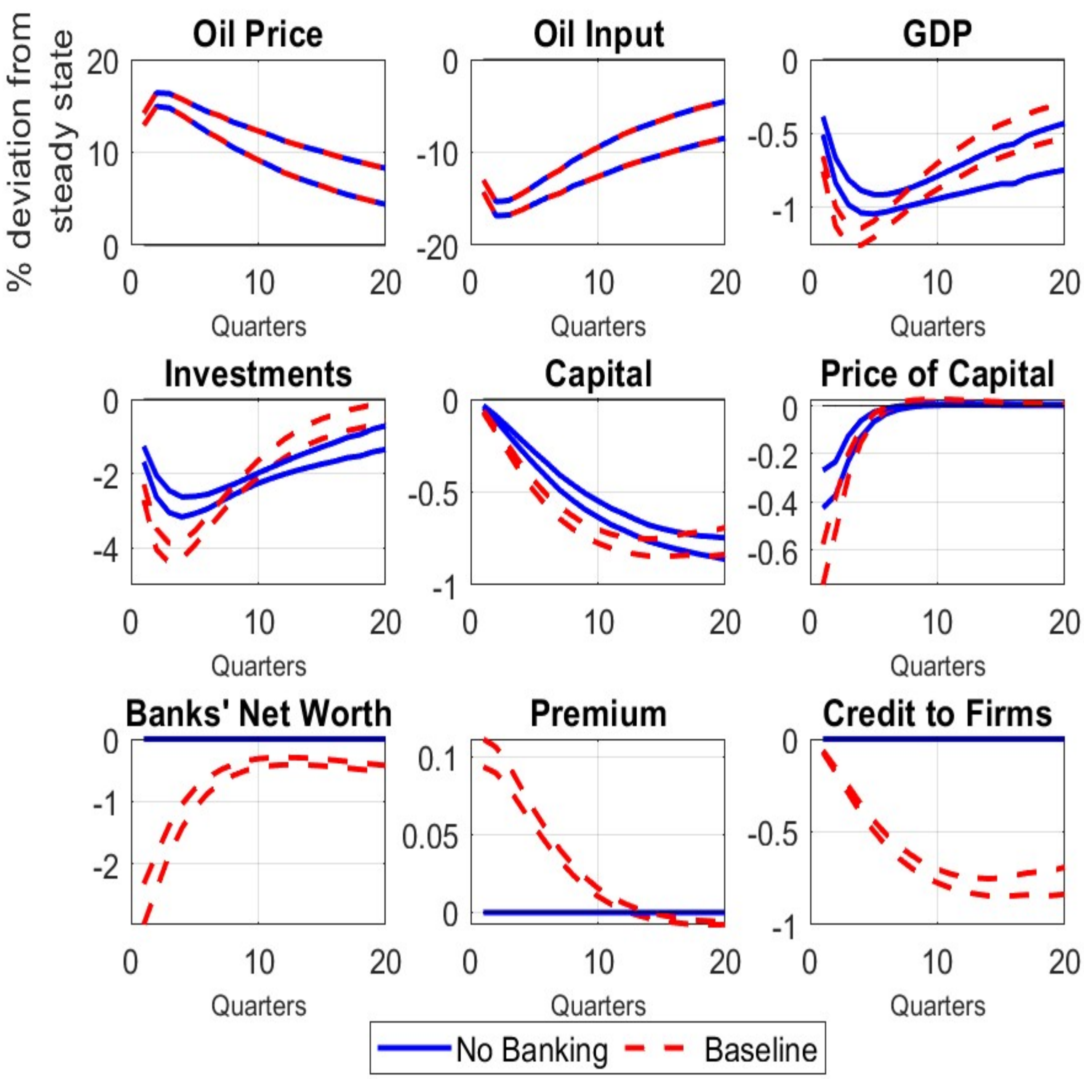
$$\frac{1}{\phi_{r,t}} = \Phi_t \frac{1}{\phi_{c,t}} \qquad \rightarrow \qquad \Phi_t = \frac{\phi_{c,t}}{\phi_{r,t}} \tag{59}$$

F 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.

F.1 Long Sample

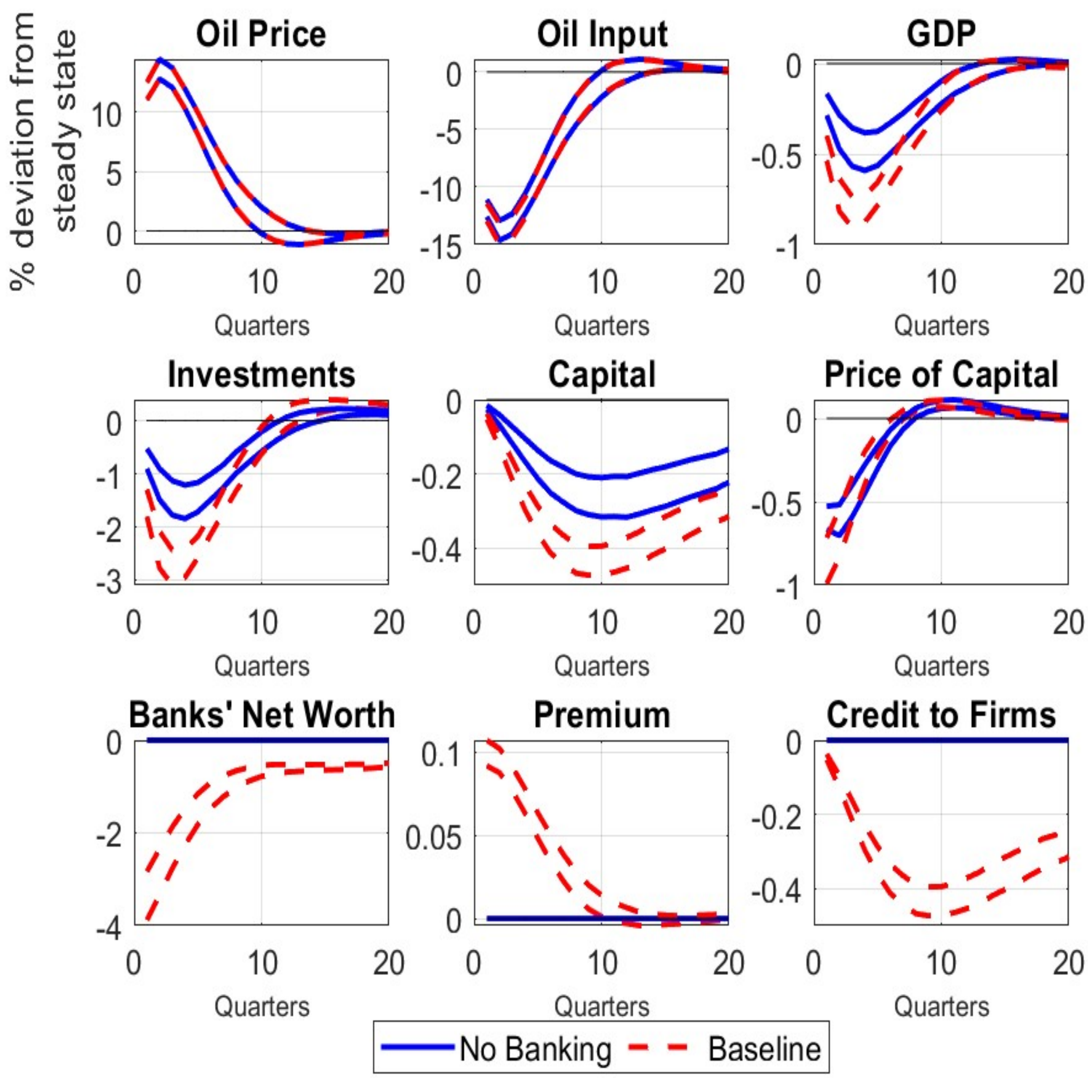
Figure E1: **Oil price shock dynamics - Long sample**



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' distribution 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 1974Q1-2019Q4.

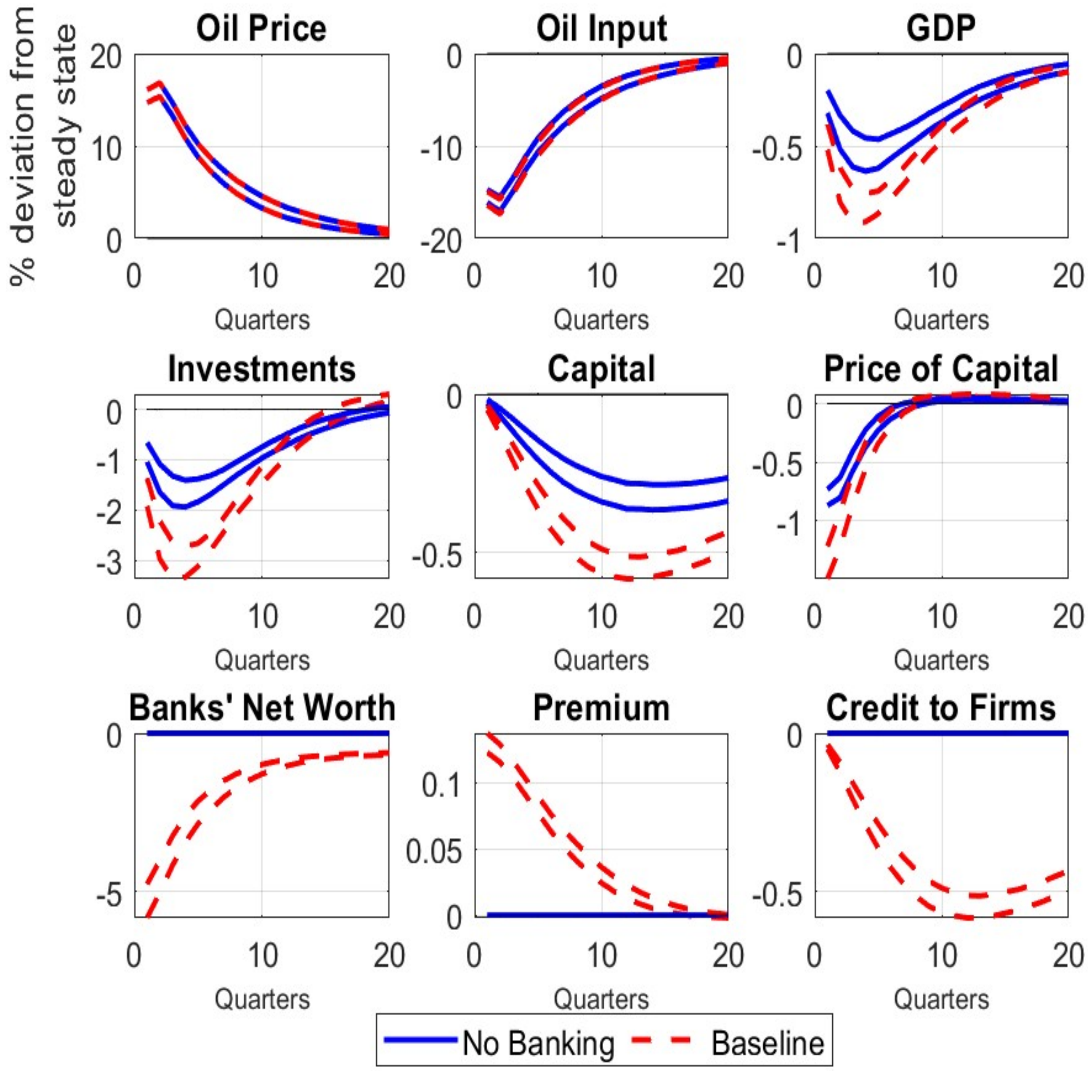
F.2 Stationarity of the oil price

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 $5th$ and $95th$ percentiles of the responses' distribution 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.

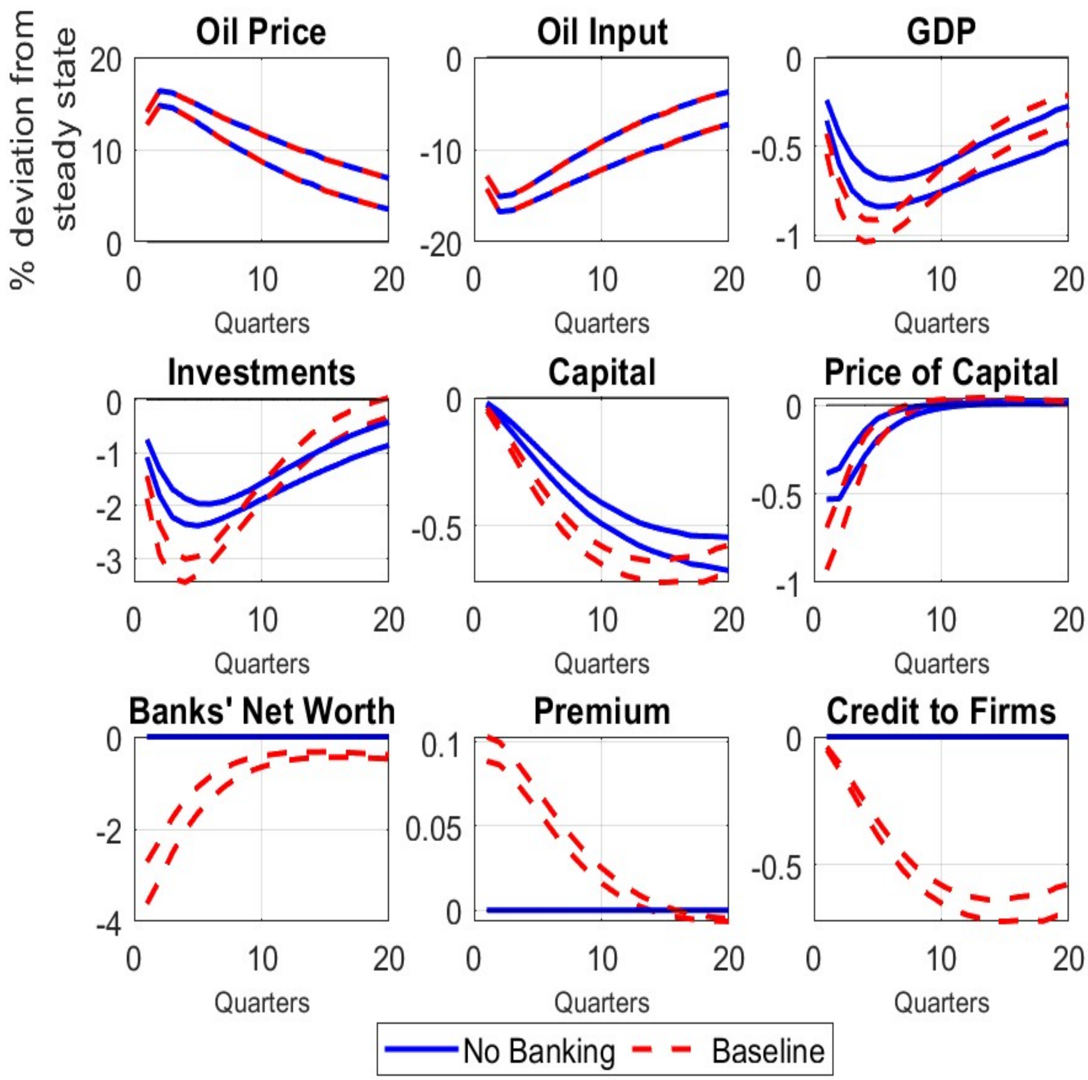
Figure E3: **Oil price shock dynamics (sample 2005Q1–2019Q4)**



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' distribution 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.

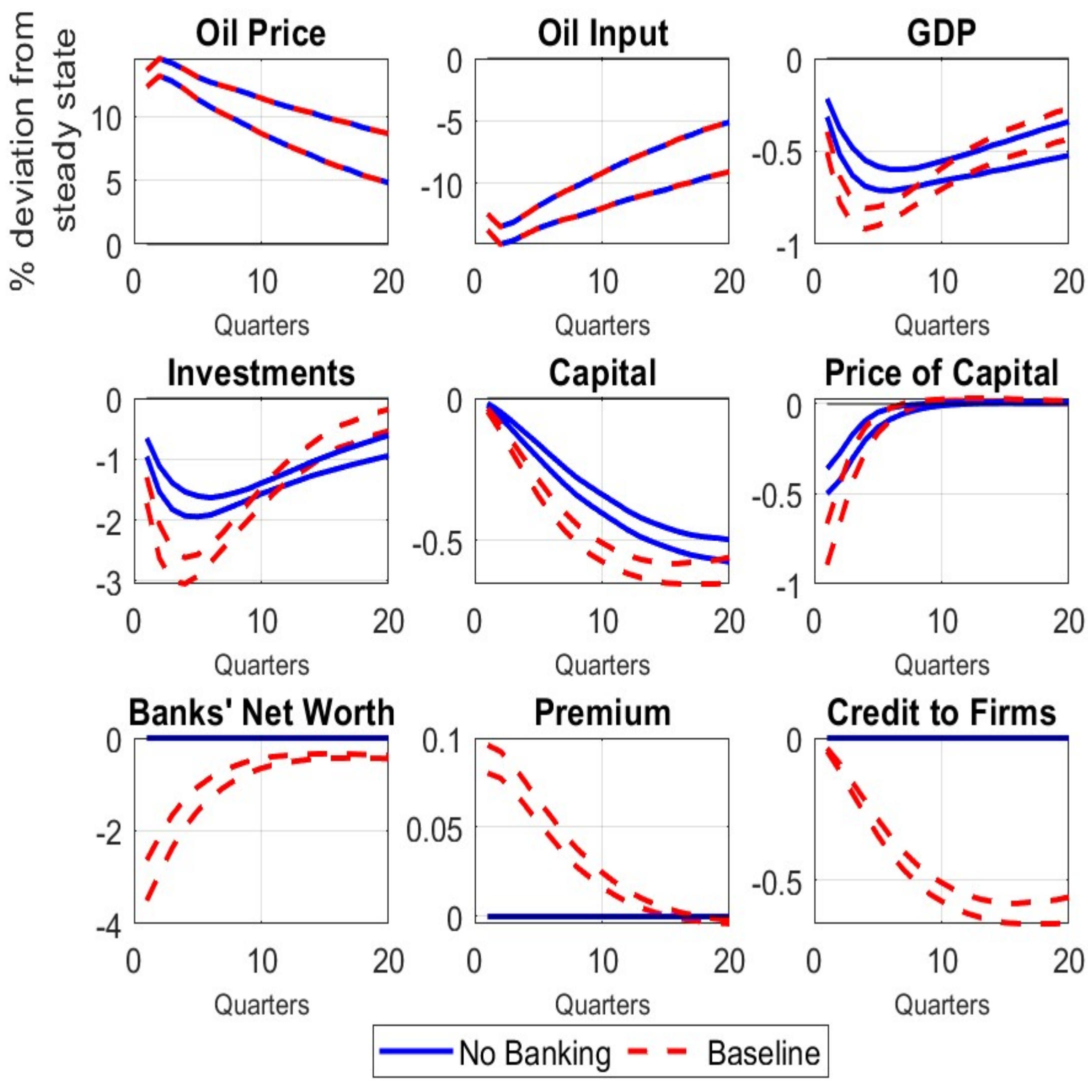
F.3 Observables

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' distribution 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.

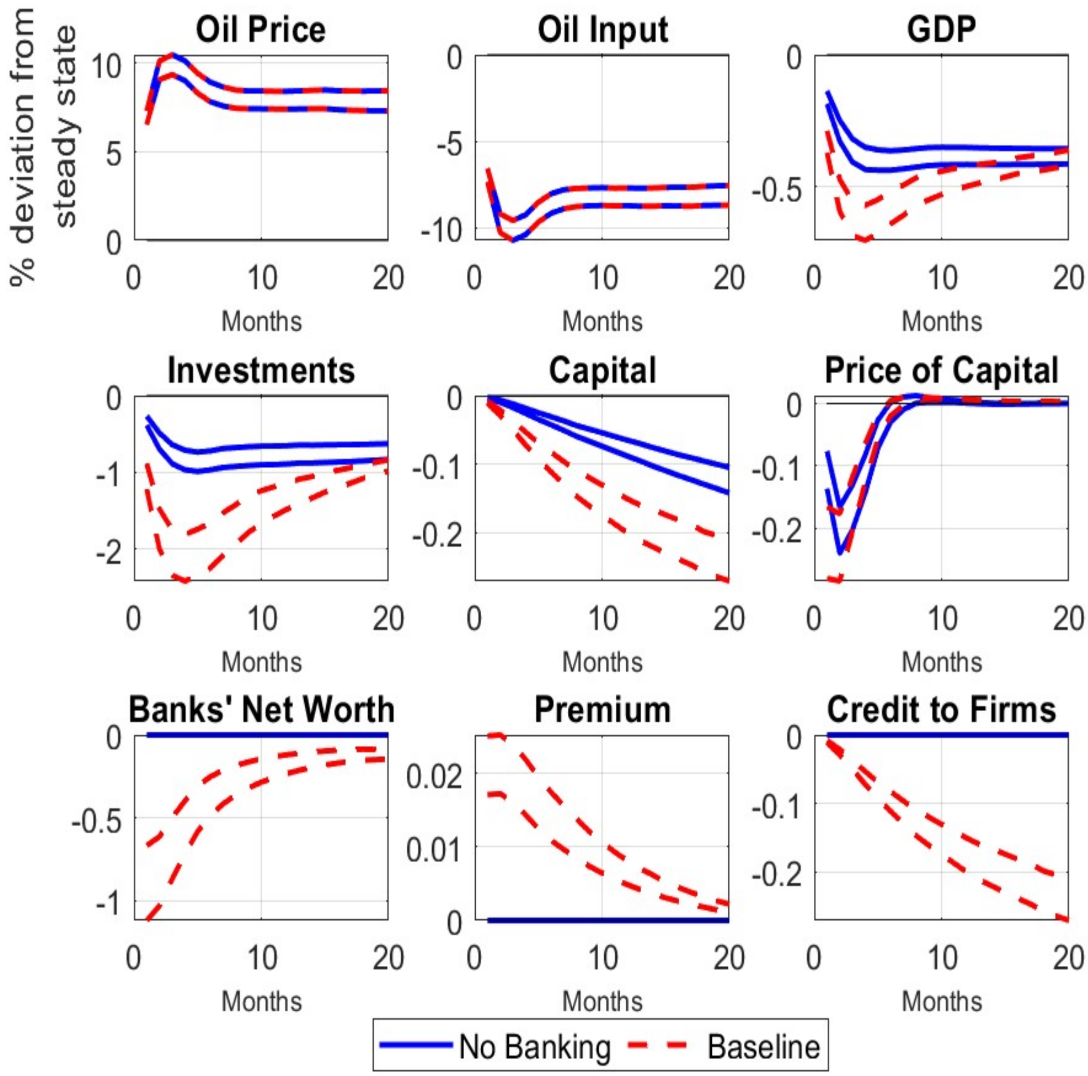
Figure E5: **Oil price shock dynamics (GECON Index)**



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' distribution 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.

F.4 Frequency

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' distribution for each variable. The solid lines indicate an RBC model with oil only, whereas the dashed red lines correspond to our baseline model.

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

[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.

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.

F.5 SVAR specification

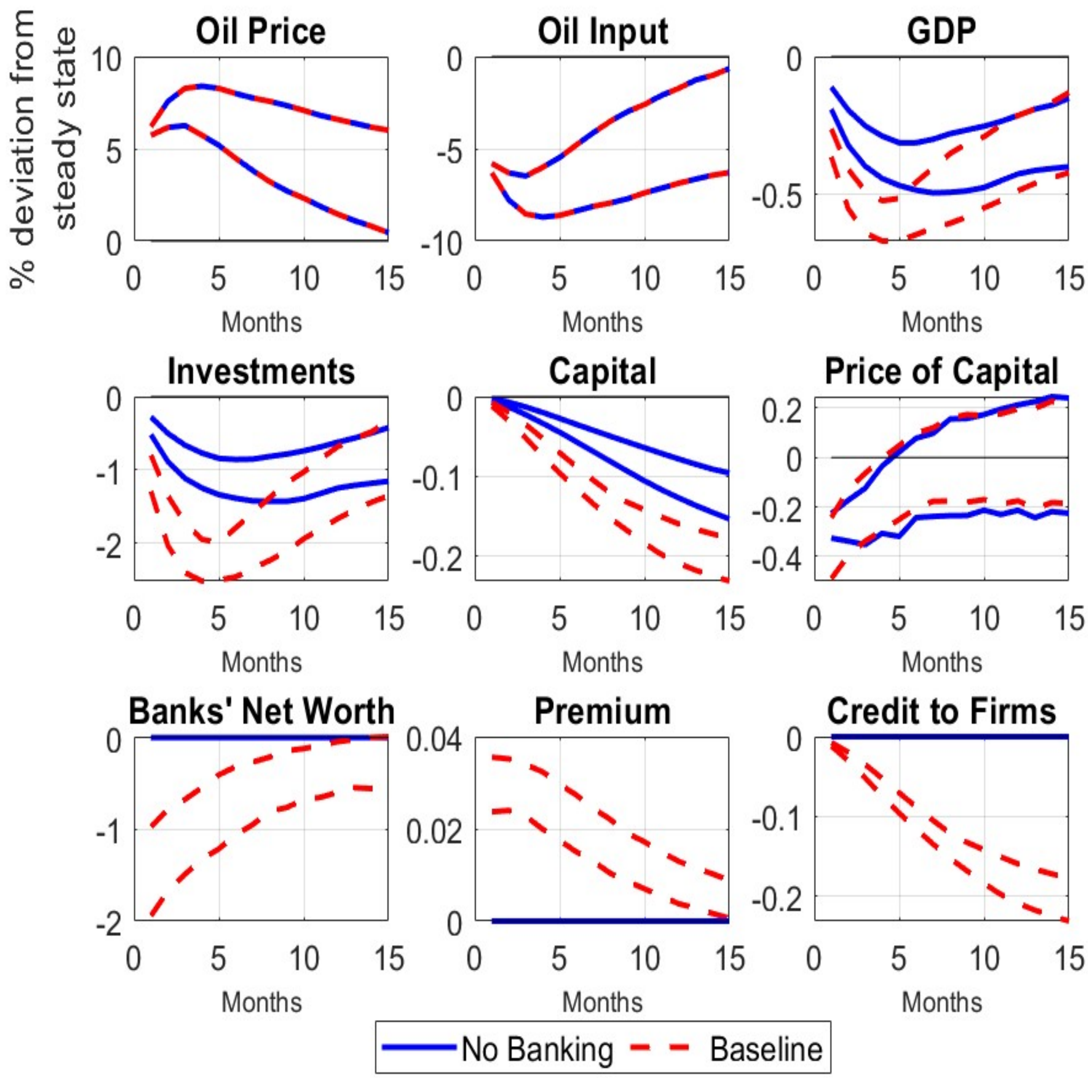
In this Appendix, we report the impulse response functions and the variance decomposition of the price of oil and of real per capita GDP growth from the models with all the alternative SVAR specifications. The former variance decomposition is relevant to highlight the main drivers of the price of oil in each SVAR specification. For the sake of completeness and comparison, we start by reporting the variance decomposition of the price of oil of our baseline model that we did not report elsewhere.

Table E1: **Price of oil variance decomposition**

Shock	Percent
1 quarter ahead	
Global Real Economic Activity	9.78
Oil Price	90.22
4 quarters ahead	
Global Real Economic Activity	9.69
Oil Price	90.31
16 quarters ahead	
Global Real Economic Activity	9.64
Oil Price	90.36
Infinity	
Global Real Economic Activity	9.63
Oil Price	90.37

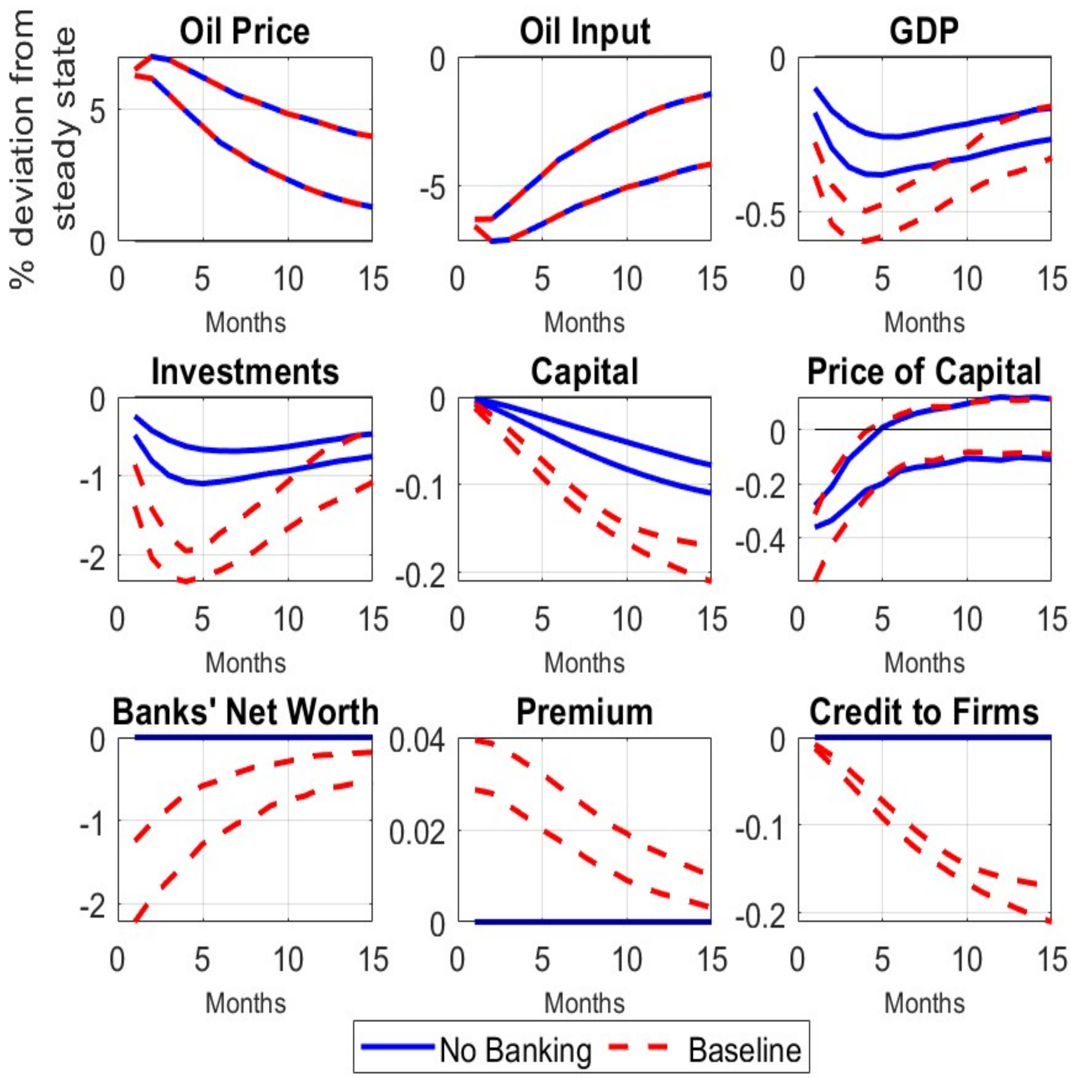
Notes: The table shows the price of oil variance decomposition for different horizons for our baseline analysis. The variance decomposition for the price of oil is identical across the DSGE model specifications.

Figure E7: **Oil supply shock dynamics with Caldara et al. (2019)**



Notes: The figure shows the impulse response functions of the key variables to an estimated one standard deviation shock to the oil supply as estimated in Caldara et al. (2019). The graphs report the 90 percent pointwise credible sets of the responses' distribution for each variable. The solid blue lines indicate an RBC model with oil only, and the dashed red lines correspond to our baseline model. Estimation sample: 1985M1-2015M12.

Figure E8: **Oil demand shock dynamics with Caldara et al. (2019)**



Notes: The figure shows the impulse response functions of the key variables to an estimated one standard deviation shock to the oil demand as estimated in Caldara et al. (2019). The graphs report the 90 percent pointwise credible sets of the responses' distribution for each variable. The solid blue lines indicate an RBC model with oil only, and the dashed red lines correspond to our baseline model. Estimation sample: 1985M1-2015M12.

Table E2: **Price of oil variance decomposition with Caldara et al. (2019)**

Shock	
1 quarter ahead	
Oil Supply	44.91
Oil Demand	51.97
Other Shocks	2.12
4 quarters ahead	
Oil Supply	47.81
Oil Demand	40.08
Other Shocks	12.1
16 quarters ahead	
Oil Supply	39.42
Oil Demand	28.27
Other Shocks	32.31
Infinity	
Oil Supply	32.39
Oil Demand	25.36
Other Shocks	42.25

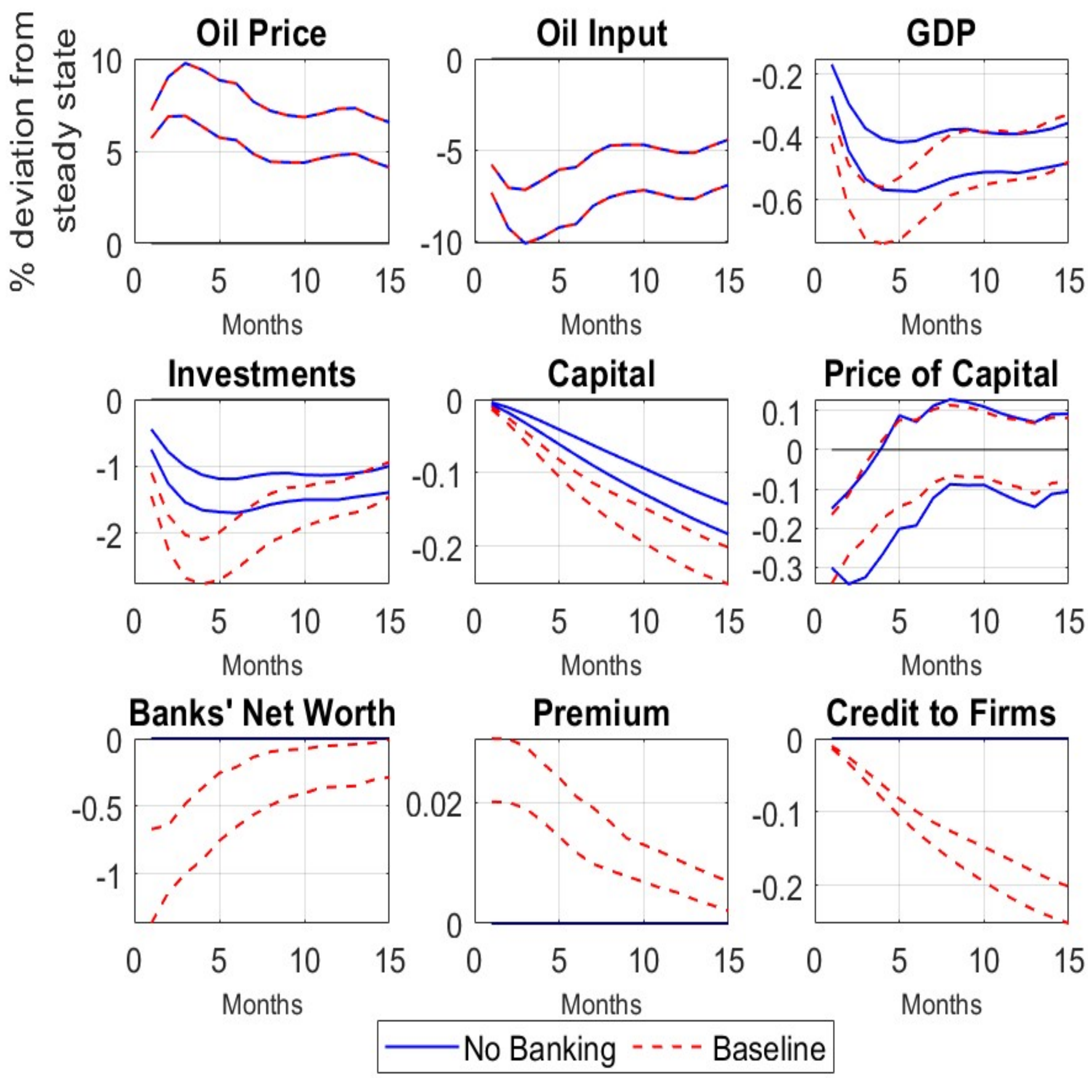
Notes: The table shows the price of oil variance decomposition for different horizons with the SVAR specified as in Caldara et al. (2019). The variance decomposition for the price of oil is identical across the DSGE model specifications. "Other Shocks" are: "Advanced economies activity", "Emerging economies activity", and "Metal prices". Estimation sample: 1985M1-2015M12. Consistently with this reference, we compute the variance decomposition by computing its distribution from the impulse response functions' distributions. We report here the 50*th* percentile.

Table E3: **GDP growth variance decomposition with Caldara et al. (2019)**

Shock	Oil and No Banking	Baseline
1 quarter ahead		
Technology, ε_t^z	67.43	51.62
Quality of Capital, ε_t^ξ	1.09	21.69
Government Spending, ε_t^g	24.02	4.86
Divert, ε_t^λ	–	3.44
Banks' Net Worth, ε_t^θ	–	0.10
Oil Supply	3.64	8.48
Oil Demand	3.07	9.20
Other Shocks	0.74	0.60
4 quarters ahead		
Technology, ε_t^z	67.40	49.27
Quality of Capital, ε_t^ξ	1.06	21.49
Government Spending, ε_t^g	20.17	4.85
Divert, ε_t^λ	–	3.69
Banks' Net Worth, ε_t^θ	–	0.55
Oil Supply	5.35	9.40
Oil Demand	3.93	9.24
Other Shocks	2.09	1.49
16 quarters ahead		
Technology, ε_t^z	66.74	47.26
Quality of Capital, ε_t^ξ	1.14	21.93
Government Spending, ε_t^g	19.78	4.65
Divert, ε_t^λ	–	3.98
Banks' Net Worth, ε_t^θ	–	1.10
Oil Supply	5.56	9.75
Oil Demand	3.96	9.40
Other Shocks	2.82	1.93
Infinity		
Technology, ε_t^z	66.37	46.97
Quality of Capital, ε_t^ξ	1.13	22.03
Government Spending, ε_t^g	19.69	4.62
Divert, ε_t^λ	–	4.02
Banks' Net Worth, ε_t^θ	–	1.13
Oil Supply	5.72	9.81
Oil Demand	4.02	9.41
Other Shocks	3.06	2.01

Notes: The table shows the real per capita GDP growth variance decomposition for different horizons for the RBC model plus the oil sector (first column), and our baseline model with both the oil and the banking sectors (second column), both with the SVAR specified as in Caldara et al. (2019). "Other Shocks" are: "Advanced economies activity", "Emerging economies activity", and "Metal prices". Estimation sample: 1985M1-2015M12. Consistently with this reference, we compute the variance decomposition by computing its distribution from the impulse response functions' distributions. We report here the $50th$ percentile.

Figure E9: **Oil supply news shock dynamics with Känzig (2021)**



Notes: The figure shows the impulse response functions of the key variables to an estimated one standard deviation oil supply news shock as estimated in Känzig (2021). The graphs report the 68 percent confidence bands of the responses distribution for each variable. The solid blue lines indicate an RBC model with oil only, and the dashed red lines correspond to our baseline model. Estimation sample: 1974M1-2017M12.

Table E4: **Price of oil variance decomposition with Känzig (2021)**

Shock	
1 quarter ahead	
Oil Supply News	83
Other Shocks	17
4 quarters ahead	
Oil Supply News	78
Other Shocks	22
16 quarters ahead	
Oil Supply News	76
Other Shocks	24
Infinity	
Oil Supply News	69
Other Shocks	31

Notes: The table shows the price of oil variance decomposition for different horizons with the SVAR specified as in Känzig (2021). The variance decomposition for the price of oil is identical across the DSGE model specifications. "Other Shocks" are: "World oil production", "World oil inventories", "World industrial production", "US industrial production", and "US CPI". Estimation sample: 1974M1-2017M12. The variance decomposition is based on Känzig (2021)'s SVAR with 6 variables, i.e., the real price of oil, world oil production, world oil inventories, world industrial production, US industrial production, and the US consumer price index (CPI). Consistently with this reference, we compute the variance decomposition by computing its distribution from the impulse response functions' distributions. We report here the $50th$ percentile.

Table E5: **GDP growth variance decomposition with Känzig (2021)**

Shock	Oil and No Banking	Baseline
1 quarter ahead		
Technology, ε_t^z	75.26	55.17
Quality of Capital, ε_t^ξ	0.69	24.55
Government Spending, ε_t^g	16.47	3.95
Divert, ε_t^λ	–	4.38
Banks' Net Worth, ε_t^θ	–	0.06
Oil Supply News	7.45	11.84
Other Shocks	0.12	0.05
4 quarters ahead		
Technology, ε_t^z	73.95	52.96
Quality of Capital, ε_t^ξ	0.62	24.11
Government Spending, ε_t^g	14.57	3.74
Divert, ε_t^λ	–	4.58
Banks' Net Worth, ε_t^θ	–	0.50
Oil Supply News	9.88	13.39
Other Shocks	0.97	0.73
16 quarters ahead		
Technology, ε_t^z	73.16	50.98
Quality of Capital, ε_t^ξ	0.66	24.57
Government Spending, ε_t^g	14.44	3.60
Divert, ε_t^λ	–	4.91
Banks' Net Worth, ε_t^θ	–	0.99
Oil Supply News	9.90	13.45
Other Shocks	1.83	1.53
Infinity		
Technology, ε_t^z	72.67	50.66
Quality of Capital, ε_t^ξ	0.66	24.58
Government Spending, ε_t^g	14.36	3.58
Divert, ε_t^λ	–	4.92
Banks' Net Worth, ε_t^θ	–	1.02
Oil Supply News	10.23	13.59
Other Shocks	2.10	1.65

Notes: The table shows the real per capita GDP growth variance decomposition for different horizons for the RBC model plus the oil sector (first column), and our baseline model with both the oil and the banking sectors (second column), both with the SVAR specified as in Känzig (2021). "Other Shocks" are: "World oil production", "World oil inventories", "World industrial production", "US industrial production", and "US CPI". Estimation sample: 1974M1-2017M12. The variance decomposition is based on Känzig (2021)'s SVAR with 6 variables, i.e., the real price of oil, world oil production, world oil inventories, world industrial production, US industrial production, and the US consumer price index (CPI). Consistently with this reference, we compute the variance decomposition by computing its distribution from the impulse response functions' distributions. We report here the 50*th* percentile.

F.6 Nominal rigidities and monetary policy

In this section, we report the new equilibrium conditions due to the introduction of nominal rigidities. Also, we enlarge the set of observables we use to estimate the model. We include the inflation rate, the federal funds rate, wage growth, and hours worked. As a result, we introduce additional shocks, i.e., the preference shock, the labor supply shock, the price markup shock, and the inflation target shock. We show how the relevant equilibrium conditions are modified. Finally, the marginal cost P_{mt} is not constant anymore, but it is endogenously determined. In the steady state it is equal to the inverse of the price markup. The equations in which it appears are:

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

$$W_t=P_{mt}\alpha\frac{Y_t}{L_t}$$

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

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

As for the introduction of the preference shock b_t and the labor supply shock χ_t, the labor supply equation and the Euler equation are modified as follows:

$$\Psi_t W_t=b_t\chi_t L_t^{\varphi}$$

$$\Psi_t\equiv b_t\left(C_t-hC_{t-1}\right)^{-1}-\beta hE_t\left[b_{t+1}\left(C_{t+1}-hC_t\right)^{-1}\right]$$

where $\ln b_t=\rho_b\ln b_{t-1}+\sigma_b\varepsilon_t^b$, $\ln\chi_t=(1-\rho_\chi)\ln\chi+\rho_\chi\ln\chi_{t-1}+\sigma_\chi\varepsilon_t^\chi$ and ε_t^b and ε_t^χ are independently and identically distributed $N(0,1)$ innovations. Following Faccini and Melosi (2022), to account for the low frequency movements in hours worked we set ρ_χ to be equal to 0.995.

The introduction of nominal rigidities implies that the final-good-producers in our baseline model become intermediate goods firms. The final-good-producers, or retailers, produce instead the final output Y_t. That is a CES composite of a continuum of mass unity of differentiated retail firms (with elasticity of substitution ε), that use intermediate output, Y_{mt}, as the sole input.

Retailers simply re-package intermediate output. It takes one unit of intermediate output to make a unit of retail output. The marginal cost is thus the relative intermediate output price P_{mt}. Each period a firm is able to freely adjust its price with probability $(1-\gamma_c)$. In between these periods, the firm is able to index its price to the lagged rate of inflation with intensity γ_p. The retailers' pricing problem then is to choose the optimal reset price P_t^* to solve their maximization problem. The resulting equations are:

wholesale, retail output:

$$Y_t=Y_mD_t$$

price dispersion ($\Pi_t = P_t/P_{t-1}$):

$$D_t = \gamma_c D_{t-1} \Pi_{t-1}^{\gamma_p \varepsilon} \Pi_t^{\varepsilon} + (1-\gamma_c) \left(\frac{1 - \gamma_c \Pi_{t-1}^{\gamma_p(1-\gamma_c)} \Pi_t^{\gamma_c - 1}}{1-\gamma_c} \right)^{-\frac{\varepsilon}{1-\gamma_c}}$$

recursive formulation of optimal choice ($\Pi_t^* = P_t^*/P_{t-1}$):

$$F_{1,t} = \lambda_{\pi,t} Y_t P_{mt} + E_t \left[\beta \gamma_c \Lambda_{t,t+1} \frac{\Pi_t^{-\gamma_p \varepsilon}}{\Pi_{t+1}^{-\varepsilon}} F_{1,t+1} \right]$$

$$F_{2,t} = Y_t + E_t \left[\beta \gamma_c \Lambda_{t,t+1} \frac{\Pi_t^{\gamma_p(1-\varepsilon)}}{\Pi_{t+1}^{(1-\varepsilon)}} F_{2,t+1} \right]$$

$$\Pi_t^* = \frac{\varepsilon}{\varepsilon - 1} \frac{F_{1,t}}{F_{2,t}} \Pi_t$$

Following Smets and Wouters (2007), we specify the following stochastic process for the price markup shock:

$$\ln \lambda_{\pi,t} = \rho_\pi \ln \lambda_{\pi,t-1} + \sigma_\pi \varepsilon_t^\pi - \mu_\pi \sigma_\pi \varepsilon_{t-1}^\pi$$

where ε_t^π is an independently and identically distributed $N(0,1)$ innovation.

Inflation development:

$$\Pi_t^{(1-\varepsilon)} = \gamma_c \Pi_{t-1}^{\gamma_p(1-\varepsilon)} + (1-\gamma_c) \Pi_t^{*1-\varepsilon}$$

Fisher equation:

$$i_t^{mp} = \ln R_{t+1} + E_t \pi_{t+1}$$

Finally, monetary policy is modeled as the following Taylor-type rule for the nominal interest rate:

$$i_t^{mp} = \rho_i i_{t-1}^{mp} + (1-\rho_i) \left[R + \frac{\kappa_\pi}{4} (\pi_t + \pi_{t-1} + \pi_{t-2} + \pi_{t-3} - \ln \pi_t^*) + \frac{\kappa_y}{4} (\ln Y_t - \ln Y_{t-4}) \right] + \sigma_i \varepsilon_t^i$$

where ε_t^i is an independently and identically distributed $N(0,1)$ monetary policy shock, $\ln \pi_t^* = \rho_* \ln \pi_{t-1}^* + \sigma_* \varepsilon_t^*$ is the inflation target shock, and ε_t^* is an independently and identically distributed $N(0,1)$ innovation. Following the common practice in the literature, e.g., Justiniano et al. (2013), we set ρ_* to be equal to 0.995.

Finally, the measurement equations for the new observables:

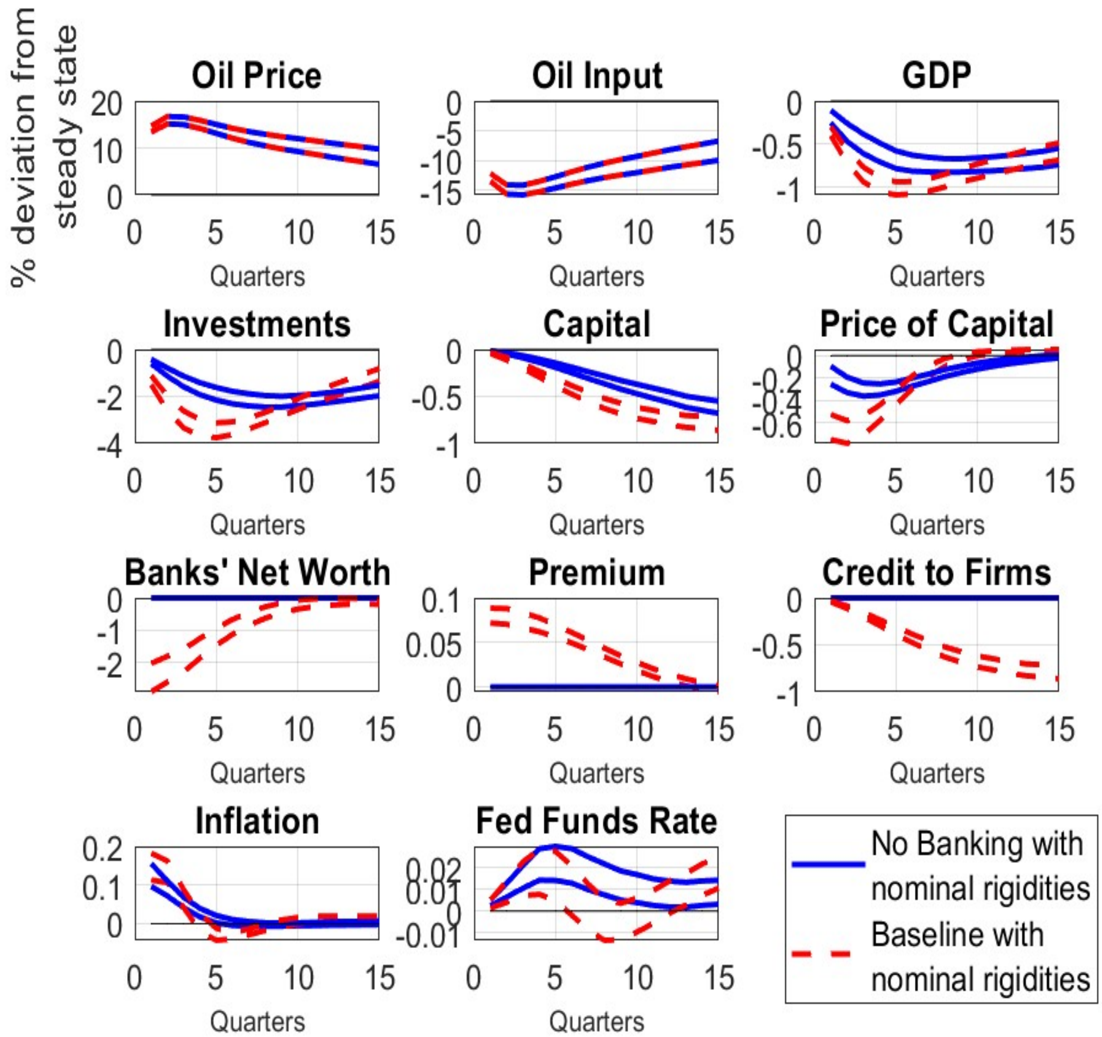
$$\begin{aligned}
\text{Fed funds rate} &= i_t \\
\text{Inflation rate} &= \pi_t \\
\text{Hours worked} &= L_t \\
\text{Wage growth} &= \ln w_t - \ln w_{t-1} + z_t
\end{aligned}$$

Table E6: **Prior and posterior distributions in the models with nominal rigidities**

Parameter				**Oil No Banking**	**Oil Banking (New Keynesian Baseline)**
	Prior	Mean	St. Dev.	Post. Mode	Post. Mode
σ_z	IG	0.100	3.00	1.7273	1.7144
σ_ξ	IG	0.100	3.00	3.6614	1.9114
σ_g	IG	0.100	3.00	2.0424	2.0022
σ_θ	IG	0.100	3.00	–	0.5887
σ_λ	IG	0.100	3.00	–	1.3106
σ_{P_o}	N	14.859	0.5	14.6621	14.7813
σ_W	N	0.352	0.5	0.3514	0.3383
ρ_z	B	0.500	0.20	0.5542	0.1615
ρ_ξ	B	0.500	0.20	0.0086	0.2953
ρ_g	B	0.500	0.20	0.9144	0.9174
ρ_θ	B	0.500	0.20	–	0.9560
ρ_λ	B	0.500	0.20	–	0.9658
h	B	0.500	0.20	0.5802	0.6514
η_i	G	4.000	1.00	3.3286	1.9285
$b_{1,1}$	N	0.632	0.005	0.6311	0.6289
$b_{1,2}$	N	-0.126	0.005	-0.1262	-0.1272
$b_{1,3}$	N	0.003	0.001	0.0030	0.0028
$b_{1,4}$	N	-0.005	0.001	-0.0048	-0.0044
$b_{2,1}$	N	4.773	0.005	4.7719	4.7713
$b_{2,2}$	N	-4.840	0.005	-4.8417	-4.8390
$b_{2,3}$	N	1.1350	0.005	1.1368	1.1321
$b_{2,4}$	N	-0.1790	0.005	-0.1782	-0.1793
$corr(u_t^W, u_t^{P_o})$	N	0.314	0.005	0.3136	0.3129
New parameters					
σ_b	IG	0.100	3.00	3.0859	2.1385
σ_i	IG	0.100	3.00	0.1089	0.1120
σ_χ	IG	0.100	3.00	1.8621	1.5473
σ_π	IG	0.050	0.03	0.0728	2.7020
σ_*	IG	0.100	3.00	0.1484	0.0435
ρ_b	B	0.500	0.20	0.6178	0.9789
ρ_π	B	0.500	0.20	0.5411	0.9176
μ_π	B	0.500	0.20	0.5231	0.7261
$100(\beta^{-1}-1)$	B	0.250	0.10	1.3597	0.0484
γ_c	B	0.500	0.20	0.7428	0.6185
γ_p	B	0.500	0.20	0.0207	0.7994
κ_π	N	1.700	0.30	1.8908	1.6037
κ_y	N	0.400	0.30	0.4297	0.3990
ρ_i	B	0.500	0.20	0.9108	0.8563

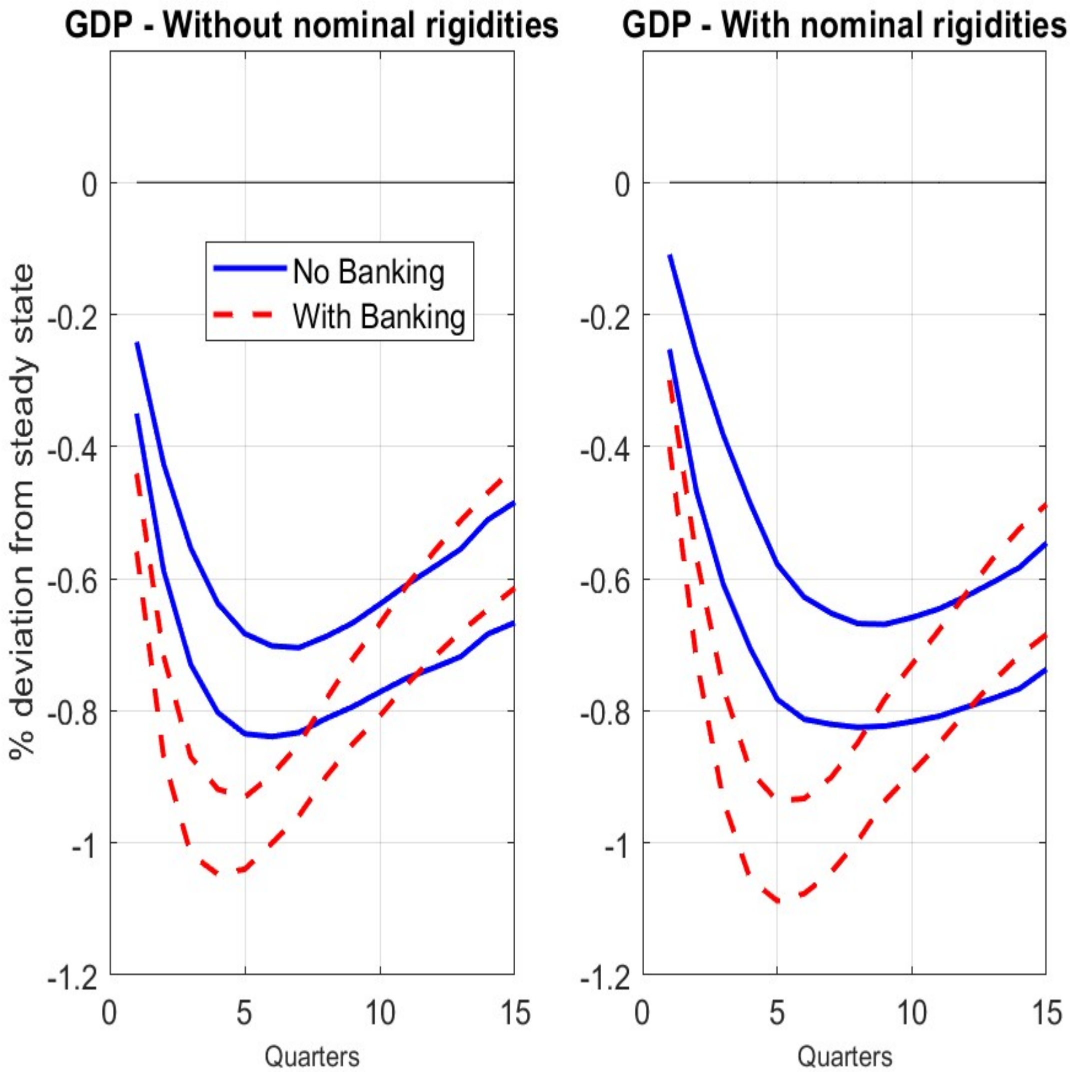
Notes: The table shows the modes of the posterior distributions of the estimated parameters in the models with nominal rigidities. We also report the means and standard deviations of the prior distributions. Regarding the prior distributions, B, N, G, and IG stand for Beta, Normal, Gamma, and Inverse Gamma, respectively. Estimates of the parameters are reported across two model specifications: New Keynesian model plus the oil sector (first column) and our New Keynesian baseline model with both the oil and the banking sectors (second column). In the interest of space the $5th$ and $95th$ percentiles are not reported. They are available upon request.

Figure E10: **Real oil price shock dynamics in the model with nominal rigidities**



Notes: The figure shows the impulse response functions of the key variables to an estimated one standard deviation shock to the real price of oil in the model with nominal rigidities. The graphs report the $5th$ and $95th$ percentiles of the responses' distribution for each variable.

Figure E11: **Real oil price shock dynamics for US GDP in models with and without nominal rigidities**



Notes: The figure shows the impulse response functions of US GDP to an estimated one standard deviation shock to the real oil price in models with and without nominal rigidities. The graphs report the $5th$ and $95th$ percentiles of the responses' distribution.

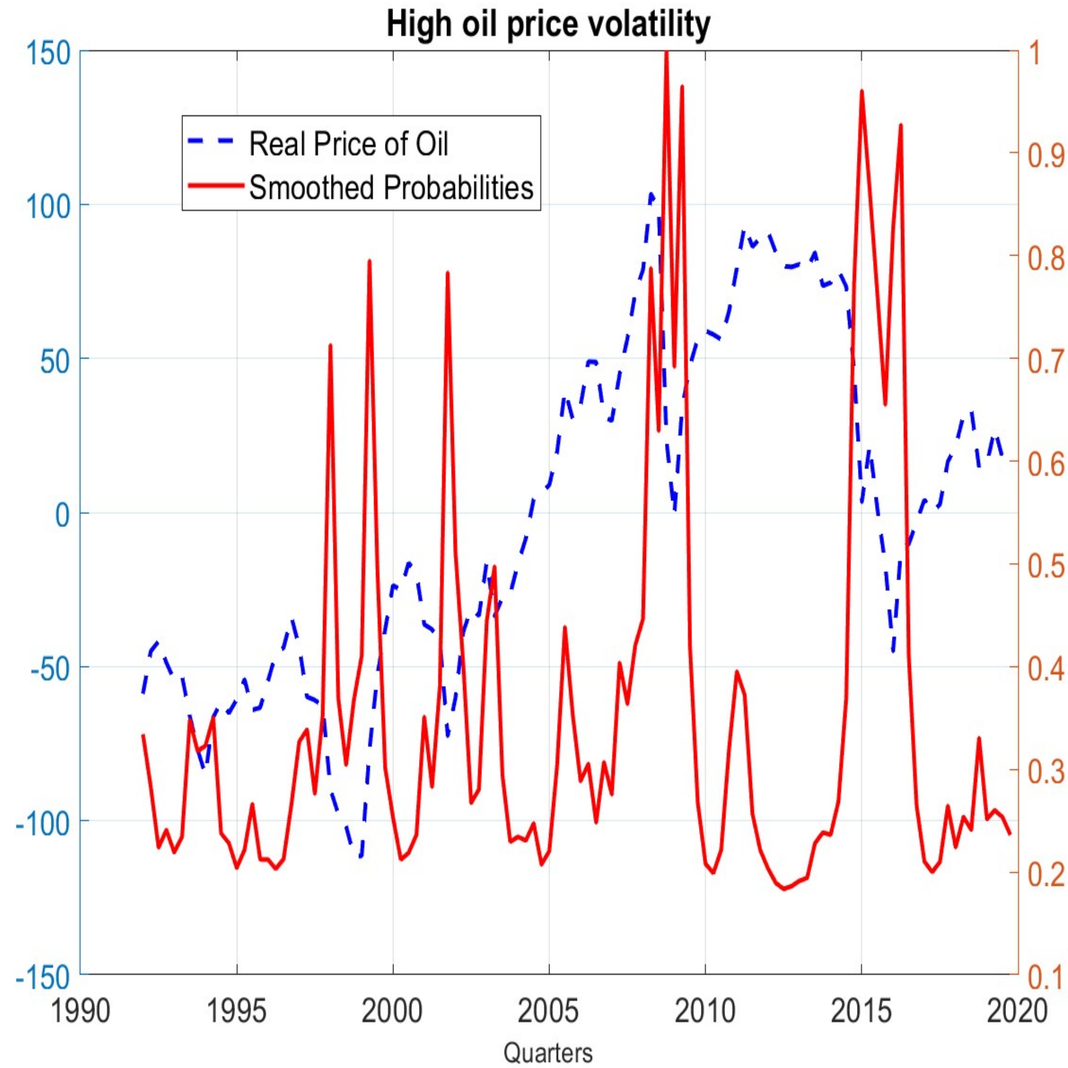
F.7 Markov Switching

Table E7: **Prior and posterior distributions in Markov Switching models**

Parameter				**Oil No Banking**	**Oil Banking (Baseline)**
	Prior	Mean	St. Dev.	Post. Mode	Post. Mode
σ_z	IG	0.100	3.00	2.3770	1.4574
σ_ξ	IG	0.100	3.00	5.5875	2.1585
σ_g	IG	0.100	3.00	3.3983	2.1281
σ_θ	IG	0.100	3.00	–	0.5493
σ_λ	IG	0.100	3.00	–	3.0612
σ_W	N	0.352	0.5	0.3448	0.3448
ρ_z	B	0.500	0.20	0.2916	0.5596
ρ_ξ	B	0.500	0.20	0.0318	0.1069
ρ_g	B	0.500	0.20	0.8946	0.9072
ρ_θ	B	0.500	0.20	–	0.9548
ρ_λ	B	0.500	0.20	–	0.9913
h	B	0.500	0.20	0.8620	0.6959
η_i	G	4.000	1.00	1.5202	1.1506
$b_{1,1}$	N	0.632	0.005	0.6318	0.6318
$b_{1,2}$	N	-0.126	0.005	-0.1257	-0.1257
$b_{1,3}$	N	0.003	0.001	0.0029	0.0029
$b_{1,4}$	N	-0.005	0.001	-0.0048	-0.0048
$b_{2,1}$	N	4.773	0.005	4.7725	4.7726
$b_{2,2}$	N	-4.840	0.005	-4.8405	-4.8405
$b_{2,3}$	N	1.1350	0.005	1.1377	1.1361
$b_{2,4}$	N	-0.1790	0.005	-0.1752	-0.1767
$corr(u_t^W, u_t^{P_o})$	N	0.314	0.005	0.3127	0.3127
$\sigma_{P_o}(S_t^{oil} = \text{High})$	N	14.859	2	17.7311	17.6837
$\sigma_{P_o}(S_t^(oil) = \text{Low})$	N	14.859	2	10.7338	10.7922
$p_{(\text{Low oil, High oil})}$	B	0.5000	0.2	0.2251	0.2306
$p_{(\text{High oil, Low oil})}$	B	0.5000	0.2	0.3982	0.4033

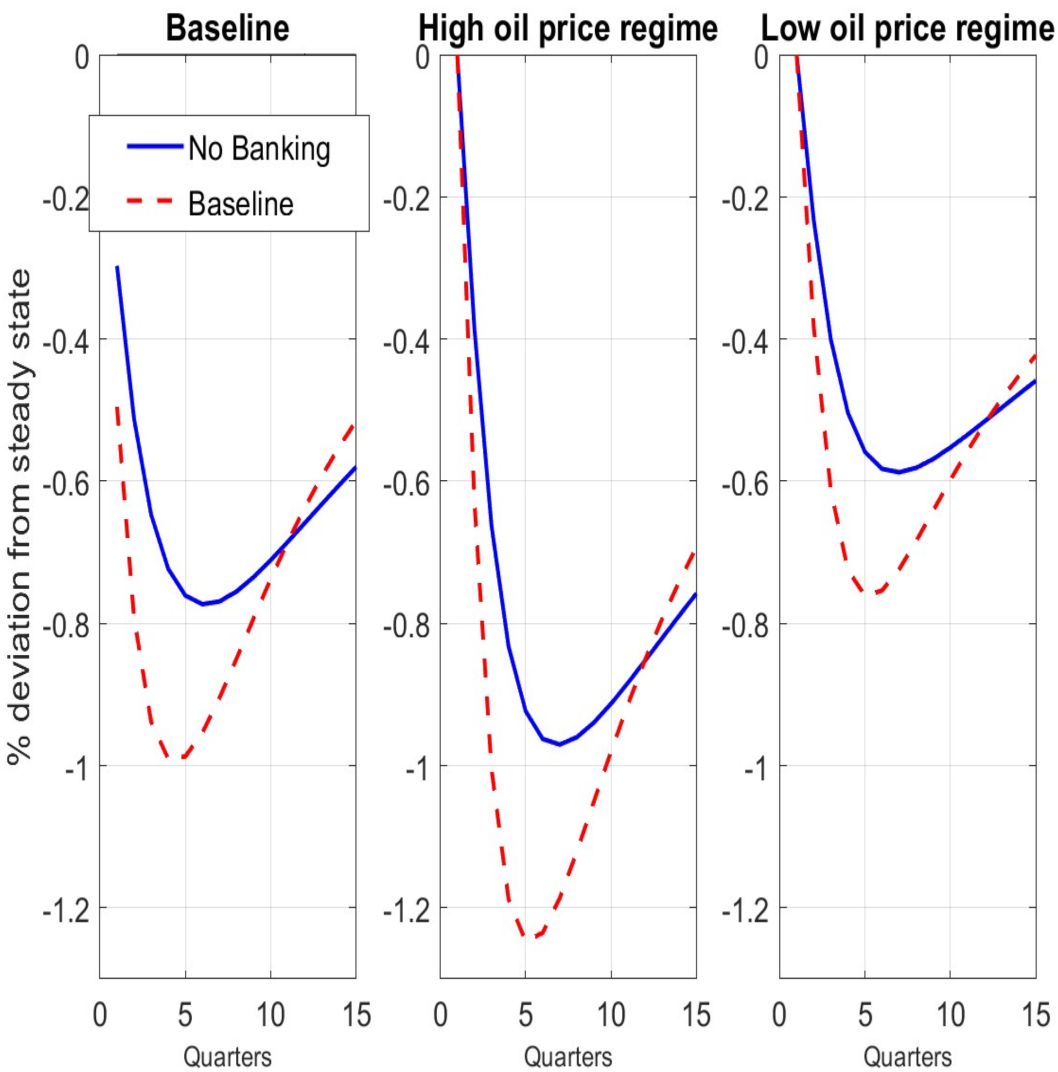
Notes: The table shows the modes of the posterior distributions of the estimated parameters in the Markov Switching environment. We also report the means and standard deviations of the prior distributions. Regarding the prior distributions, B, N, G, and IG stand for Beta, Normal, Gamma, and Inverse Gamma, respectively. Estimates of the parameters are reported across two model specifications: RBC model plus the oil sector (first column) and our baseline model with both the oil and the banking sectors (second column). In the interest of space the $5th$ and $95th$ percentiles are not reported. They are available upon request.

Figure E12: **Smoothed probabilities and the real oil price**



Notes: The figure shows the estimated smoothed probabilities of being in the high oil price volatility regime, together with the observed series of the real price of oil (demeaned). The left scale refers to the latter, while the right scale refers to the former.

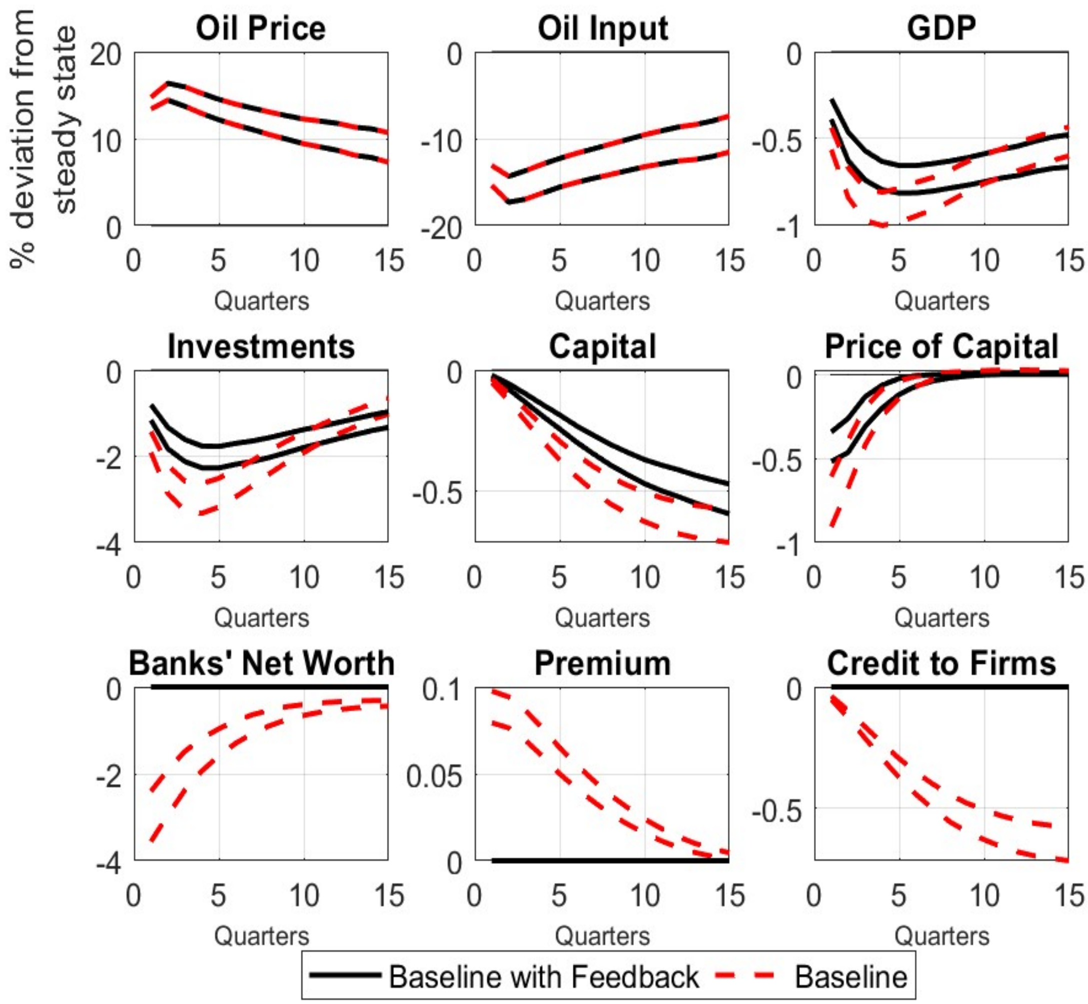
Figure E13: **GDP response to oil price shocks with and without regime switching**



Notes: The figure shows the response of US GDP to an estimated one standard deviation shock to the real oil price in our baseline model and in the model with regime switching for the two oil price volatility regimes.

F.8 Price of oil's endogeneity

Figure E14: **Oil price shock dynamics - US feedback**



Notes: The figure shows the impulse response functions of the key variables to an oil price shock for the baseline model and for a model augmented with direct feedback from the US economy to the price of oil. The graphs report the $5th$ and $95th$ percentiles of the responses' distribution 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 1974Q1-2019Q4.

Table E8: **GDP growth variance decomposition**

Shock	**Oil No Banking (RBC)**	**Oil Banking (Baseline)**
1 quarter ahead		
Technology, ε_t^z	75.28	57.54
Quality of Capital, ε_t^ξ	0.02	12.26
Government Spending, ε_t^g	18.01	5.86
Divert, ε_t^λ	–	7.65
Banks' Net Worth, ε_t^θ	–	0.08
Oil Price, $\varepsilon_t^{P_o}$	6.03	14.97
World GDP Growth, ε_t^W	0.66	1.64
4 quarters ahead		
Technology, ε_t^z	77.28	67.73
Quality of Capital, ε_t^ξ	0.02	8.49
Government Spending, ε_t^g	14.92	4.16
Divert, ε_t^λ	–	5.64
Banks' Net Worth, ε_t^θ	–	0.64
Oil Price, $\varepsilon_t^{P_o}$	7.02	12.03
World GDP Growth, ε_t^W	0.76	1.31
16 quarters ahead		
Technology, ε_t^z	77.28	67.27
Quality of Capital, ε_t^ξ	0.03	8.65
Government Spending, ε_t^g	14.85	3.97
Divert, ε_t^λ	–	5.70
Banks' Net Worth, ε_t^θ	–	1.09
Oil Price, $\varepsilon_t^{P_o}$	7.07	12.01
World GDP Growth, ε_t^W	0.77	1.31
Infinity		
Technology, ε_t^z	77.11	67.01
Quality of Capital, ε_t^ξ	0.04	8.66
Government Spending, ε_t^g	14.81	3.95
Divert, ε_t^λ	–	5.70
Banks' Net Worth, ε_t^θ	–	1.23
Oil Price, $\varepsilon_t^{P_o}$	7.26	12.13
World GDP Growth, ε_t^W	0.79	1.32

Notes: The table shows the real per capita GDP growth variance decomposition for different horizons and two different model specifications, both augmented with direct feedback from the US economy to the price of oil: RBC model plus the oil sector (first column) and our baseline model with both the oil and the banking sectors (second column). The variance decomposition is computed at the posterior modes. We also computed the variance decomposition by taking 1000 draws from the posterior distributions, such that we generate a distribution of 1000 variance decompositions. The $50th$ percentile of that distribution gives the same values reported in this table. Moreover, the distribution can be used to calculate the $5th$ and $95th$ percentiles and to show that all decompositions are statistically different. In the interest of the table's readability we do not report them. They are available upon request.

F.9 Feedback effects from the rest of the world to the US economy

To account for the feedback effects from the rest of the world to the US economy, we re-specify the US shock processes as follows:

$$\Psi_t = \underbrace{C + \Delta\Psi_{t-1} + \Omega\epsilon_t}_{\text{Baseline specification}} + \Theta\varepsilon_t^W$$

where

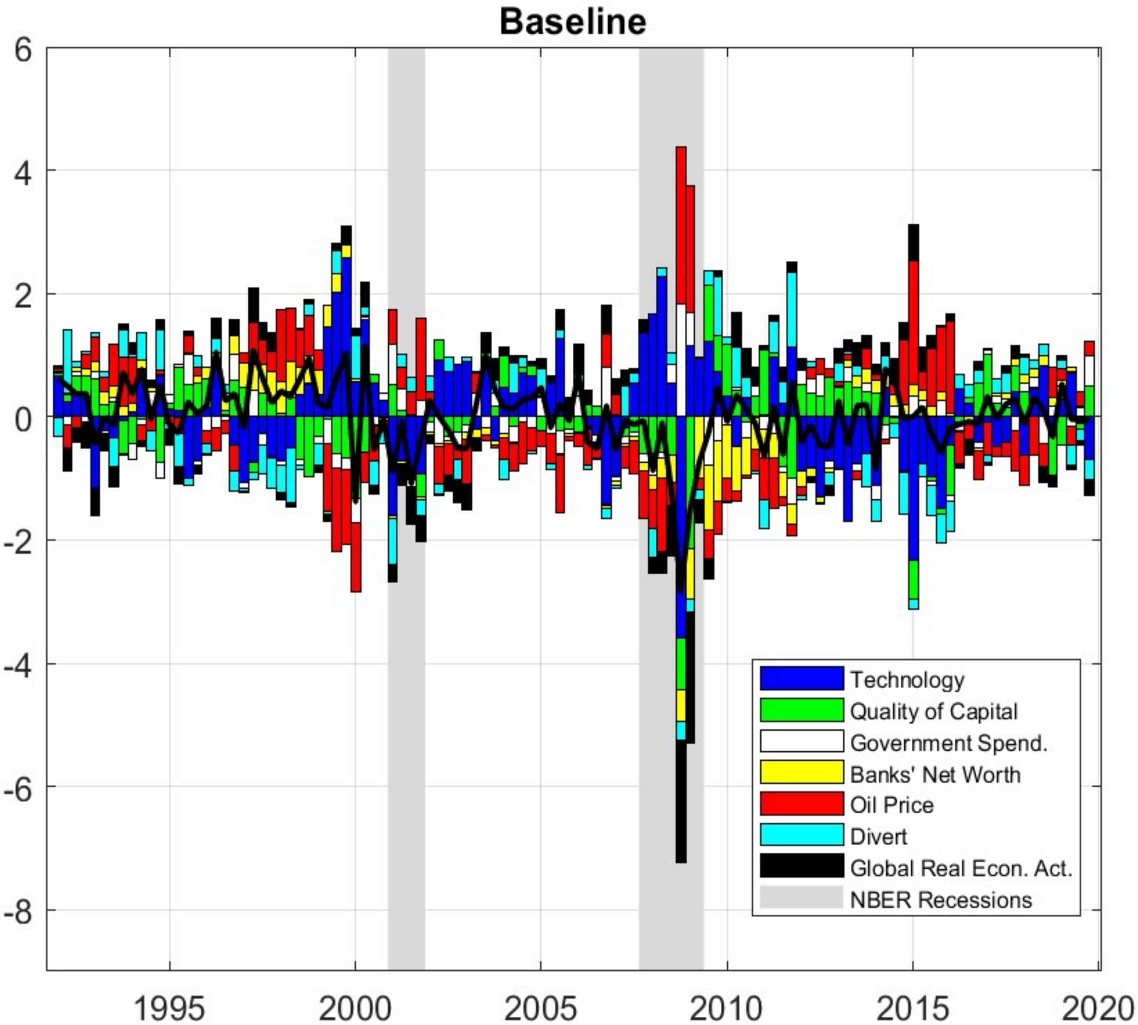
$$\Psi_t = \begin{bmatrix} z_t \\ \ln \xi_t \\ \ln G_t \\ \ln \theta_t \\ \ln \lambda_t \end{bmatrix}, C = \begin{bmatrix} (1-\rho_z)\gamma \\ (1-\rho_\xi)\ln \xi \\ (1-\rho_g)\ln g \\ (1-\rho_\theta)\ln \theta \\ (1-\rho_\lambda)\ln \lambda \end{bmatrix}, \Delta = \begin{bmatrix} \rho_z & 0 & 0 & 0 & 0 \\ 0 & \rho_\xi & 0 & 0 & 0 \\ 0 & 0 & \rho_g & 0 & 0 \\ 0 & 0 & 0 & \rho_\theta & 0 \\ 0 & 0 & 0 & 0 & \rho_\lambda \end{bmatrix},$$

$$\Omega = \begin{bmatrix} \sigma_z & 0 & 0 & 0 & 0 \\ 0 & \sigma_\xi & 0 & 0 & 0 \\ 0 & 0 & \sigma_g & 0 & 0 \\ 0 & 0 & 0 & \sigma_\theta & 0 \\ 0 & 0 & 0 & 0 & \sigma_\lambda \end{bmatrix}, \epsilon_t = \begin{bmatrix} \varepsilon_t^z \\ \varepsilon_t^\xi \\ \varepsilon_t^g \\ \varepsilon_t^\theta \\ \varepsilon_t^\lambda \end{bmatrix},$$

$$\Theta = \begin{bmatrix} (1-\rho_z)\lambda_z & 0 & 0 & 0 & 0 \\ 0 & (1-\rho_\xi)\lambda_\xi & 0 & 0 & 0 \\ 0 & 0 & (1-\rho_g)\lambda_g & 0 & 0 \\ 0 & 0 & 0 & (1-\rho_\theta)\lambda_\theta & 0 \\ 0 & 0 & 0 & 0 & (1-\rho_\lambda)\lambda_\lambda \end{bmatrix}$$

We re-estimate the model and we estimate the weights in Θ. We assign to each weight a normal distribution with zero mean and a standard deviation of one as the prior distribution. The posterior modes are: $\lambda_z = 1.6654$, $\lambda_\xi = 1.7279$, $\lambda_g = 0.1298$, $\lambda_\theta = 1.3556$, and $\lambda_\lambda = 0.2024$. All the other estimated parameters are substantially unaffected.

Figure E15: **US GDP growth historical decomposition**



Notes: The figure shows the US real per capita GDP growth historical decomposition for the baseline model augmented with the feedback from the rest of the world to the US economy. Bars of different colors indicate the several shocks in the model, and the gray areas are the US recessions as identified by the NBER.