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Whither Liquidity Shocks? Implications for R^* and Monetary Policy.

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Abstract

We show that popular models of (flight-to-) liquidity shocks rely on strongly counterfactual implications for asset returns and the composition of firms' liabilities, including the return spread between bank deposits and T-bills and the share of bank loans on corporate debt. We also uncover some counterfactual/implausible interpretations of the Fed's monetary policy stance during recession periods, as hinted by the estimated gap between policy and natural rates. By including the relevant financial variables as observables in our empirical model, we find that liquidity shocks played a negligible role and became virtually irrelevant after 2010. Our estimates also imply that the slowdown in productivity growth, not liquidity shocks, caused the post-2010 fall in the natural rate. Finally, our estimates provide a quite different interpretation of the monetary policy stance.

JEL classification: C11, C32, C54, E43, E44

keywords: natural rate of interest, DSGE models, liquidity shocks, flight-to-quality, financial frictions

1 Introduction

This paper highlights the counterfactual implications of popular modelizations of liquidity shocks, interpreted as flight-to-quality episodes. We investigate the implications that these findings have for the interpretation of the long-term interest rates' decline and for our understanding of business cycles.

Interest rates have been gradually falling for a long time in many advanced economies, including the U.S. The Great Recession episode saw a further acceleration in this downward trend, leading to an unprecedented period of policy rates at (or even below) the zero lower bound (ZLB) for several quarters. This spurred renewed attention to the concept of the natural interest rate (defined by Wicksell, 1898, as the equilibrium interest rate compatible

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with price and economic stability) and to the causes and consequences of its decline, with obvious implications for the scope of monetary policy and for the analysis of business cycles. While some authors, most notably Summers (2014), pointed to long-term factors that explain this declining trend and that may have brought about an era of "secular stagnation", others emphasized the special role played by the financial crisis (e.g. Borio, 2014).

Regardless of the longer- or shorter-run perspective, safety and liquidity have been pivotal subjects of this debate. Among the explanations behind the natural rate decline stand an increasing propensity to save, in particular through safe assets. This view, related to the global saving glut hypothesis by Bernanke (2005), argues that a scarcity of safe assets and their rising attractiveness led to a secular decline in their yields with respect to less safe instruments. On the other hand, the financial crisis revealed liquidity and safety issues in markets that were previously regarded as (close to) risk-free, as showed by Kacperczyk and Schnabl (2013) for money market funds. The associated decoupling between policy rates and returns on assets characterized by different liquidity and safety attributes paved the way for a reconsideration of monetary policy transmission mechanisms (see for instance Benigno and Benigno, 2022).

A number of papers have found liquidity shocks to be an important driver of the U.S. business cycle. Christiano et al. (2015) identify a "consumption wedge" shock, specified as a preference for safe and liquid assets, as a fundamental factor behind the Great Recession. In a model that considers endogenous growth, Anzoategui et al. (2019) show that liquidity shocks have been crucial in driving the U.S. economy to a lower productivity trend.

One approach to modeling liquidity shocks (Kiyotaki and Moore, 2012; Jermann and Quadrini, 2012) emphasizes the limited resaleability of firms' equity when entrepreneurs are subject to a borrowing constraint. Fisher (2015) offers an alternative microfoundation within a standard New Keynesian framework, showing how the Smets and Wouters (2007) risk premium shock is formally equivalent to a (time-varying) preference for holding risk-free assets. Building on the work of Krishnamurthy and Vissing-Jorgensen (2012), such preference is justified with the liquidity and safety attributes that characterize government bonds, so that a positive realization of the risk premium shock assumes the interpretation of a flight to quality. By simply turning bond holdings into an argument of the household's utility function, the microfoundation of liquidity shocks proposed by Fisher (2015) can be easily incorporated into DSGE models characterized by complex financial markets. In this regard, Lindé et al. (2016) show that introducing a financial accelerator mechanism in a standard DSGE model amplifies the transmission of liquidity shocks. Del Negro et al. (2017) (DGGT henceforth) build a model with financial frictions and further develop the specification of flight-to-quality shocks, distinguishing between safety and liquidity; their results ascribe to these two components a fundamental role in determining U.S. business cycle fluctuations.

A simple and straightforward consideration motivates our contribution. By their nature, flight-to-quality shocks affect complex financial markets where different intermediaries channel funds from households to entrepreneurs. To begin with, a liquidity shock leads households to a portfolio reallocation towards "safe" assets. This, in turn, implies that return spreads across assets must adjust. Thus, a *prima-facie* external validation for the relevance of liquidity shocks should be found in the observed patterns of these spreads. Consider for instance the characterization of liquidity shocks exploited in DGGT. According to the flight-to-quality interpretation, households shift their desired portfolio composition from bank deposits to Treasuries, and in equilibrium the deposit rate must rise relative to the return on T-bills. In fact, the liquidity shock requires a divergence between deposit and policy rates which is apparently unobservable over the sample period 1964:III-2019:IV. Panel (a) of Figure 1 plots the fed funds rate against the secondary market rate on U.S. 3-month certificates of deposits (CDs). The two series show a strong co-movement and both decline during recessions. According to Krishnamurthy and Vissing-Jorgensen (2012), Nagel (2016), and Krishnamurthy and Li (2022), observed spreads between returns on bank deposits and T-Bills are sufficient to establish that these two assets are imperfect substitutes in terms of their liquidity attributes. Still, these spreads do not show a tendency to increase around recession periods and are notably smaller than the spread implied by liquidity shocks in DGGT (see panel (b) of Figure 1).

In our view, empirical models should test the ability of liquidity shocks to predict return spreads and portfolio adjustments that are consistent with observed patterns. As pointed out in Shi (2015), this concern is justified because asset prices and returns are central to the transmission mechanism of liquidity shocks. Further, flight-to-quality shocks imply that excesses of savings are a persistent feature of business cycle fluctuations and implicitly call for a policy response that should target such asset prices and returns.

We build a business cycle model that accounts for two potential transmission mechanisms that characterize liquidity shocks. The first one follows DGGT, where a flight to quality implies that households shift out of bank deposits. The second one is based on a

Figure 1: Fed funds rate, deposit rate, and deposit spreads

Note: Panel (a): data. Panel (b): the solid line is the posterior mode of the smoothed deposit rate/fed funds rate spread (obtained with our re-estimation of DGGT); "Observed deposit spread/1": 6-month CD rate - 6-month T-bill rate (Krishnamurthy and Vissing-Jorgensen, 2012); "Observed deposit spread/2": 3-month CD rate - 3-month T-bill rate (Nagel, 2016; the same measure is considered in a robustness test by Krishnamurthy and Li, 2022). 1964:III-2019:IV.

richer financial market structure where firms, in addition to equity capital, obtain funds via bank loans and corporate bonds. Here we depart from a longstanding tradition in business cycle modeling, where financial frictions are typically associated with the existence of a single type of financial intermediary. In fact, there is evidence that firms with access to the corporate debt market also borrow from banks, and typically substitute between bank loans and non-bank financing over the business cycle (Rauh and Sufi, 2010; Adrian et al., 2013; Becker and Ivashina, 2014).

In the second version of our model, commercial banks collect funds through liquid deposits and lend to entrepreneurs; non-bank financial intermediaries (NBFIs henceforth) issue deposits that are subject to liquidity shocks, and invest in corporate bonds. In this framework, flight-to-quality shocks imply a household-portfolio reallocation out of non-bank deposits, toward bank deposits *and* T-Bills. One novel feature brought about by this assumption is that, following an adverse liquidity shock, the shift in households' portfolios toward bank deposits might favor a symmetrical change in firms' liabilities towards bank loans.[1] Our approach differs from Kiyotaki and Moore (2012), where flight-to-quality shocks hit firms' ability to raise funds and induce households to shift their portfolios towards assets that provide liquidity services. In fact, our characterization is consistent with U.S. capital markets, where bond financing to the nonfinancial corporate sector accounts for about three-fifths of total funds (De Fiore and Uhlig, 2011).

The distinctive feature of our empirical analysis is the inclusion among the observables of those financial variables that the model identifies as central to the transmission of liquidity shocks. More in detail, we first estimate an augmented version of the DGGT model that accounts for the observed time series of returns on bank deposits. Conversely, the alternative specification of our model implies that liquidity shocks impact the portfolio composition of entrepreneurs' liabilities and the return spread between deposits at banks and NBFIs. The model is therefore estimated with the addition of two observables, *i.e.* a proxy for the interest rate on non-bank deposits and the ratio between bank loans and total credit to the business sector.

The inclusion of financial variables is decisive. We cannot find a significant impact of liquidity shocks on the business cycle. The reason why this happens is indeed simple: in both versions of our model, liquidity shocks imply adjustments in asset prices and returns that are at odds with the corresponding observables added to the model. When the DGGT model is not constrained to match the observed bank deposit rate, liquidity shocks are prominent because the predicted volatility of the return spread between bank deposits and Treasuries is far larger than in the data. When the NBFI model is not constrained to match financial variables, liquidity shocks are important because the model mispredicts the observed dynamics of both the bank loans' share and the return spread between bank and non-bank deposits.

Furthermore, our results contribute to a longstanding debate on the relationship between liquidity shocks and the persistent decline in the natural interest rate. Barsky et al. (2014)

[1] The idea that households turn to bank deposits in times of market stress is consistent with the evidence in Lin (2020). First, looking at financial assets owned by U.S. households (and non-profit organizations), he finds that the shares of deposits and corporate equities tend to move in opposite directions. Second, households increase demand for deposits during stock market crashes, and investor sentiment negatively affects deposits growth above the effect of stock market returns. Lastly, variations in households' deposit holdings directly affect banks' loan supply. This last finding corroborates the transmission mechanism of liquidity shocks in our enriched model.

and Gerali and Neri (2019) use frictionless DSGE models to estimate r^*. Both find large fluctuations in the natural rate that are due to risk premium shocks, interpreted as exogenous reductions in the required return on savings. DGGT study the determinants of r^* using both time-series and DSGE models: their analysis establishes a link between the persistence of liquidity shocks and the long-term decline in the natural interest rate. Another strand of literature employs semi-structural models in the spirit of Laubach and Williams (2003) and emphasizes the role played by the productivity-growth slowdown in the long-term decline of r^* (see for instance Laubach and Williams, 2016).[2] Eggertsson et al. (2019), with a quantitative life-cycle model, similarly find that productivity contributed to dragging the natural rate down, but also point out the importance of the demographic shift, in the form of reductions in fertility and mortality (analogous findings are shared by other works in the OLG framework, *e.g.* Gagnon et al., 2021, and Jones, 2022).[3]

Relative to liquidity shocks, our model-implied estimates of r^* assign a more pronounced role to adverse technology shocks, in line with the narrative in Laubach and Williams (2016). With respect to DGGT, we also obtain significantly higher estimates of the natural interest rate during the ZLB period, consistently with Wu's (2017) discussion of DGGT.[4] As a consequence of the higher estimated natural rate, our results call for a reconsideration of the Fed interest rate policy: in contrast with common wisdom (see for instance Cúrdia, 2015, and Gerali and Neri, 2019), our estimates of the interest rate gap suggest that the interest rate policy was indeed expansionary during the last quarters of the ZLB period.

We also wish to emphasize a hitherto neglected result concerning the Fed monetary policy stance as measured by the gap between the real policy and natural rates. The DGGT-estimated r^* has the questionable implication that the policy rate gap systematically increased in recession periods since 1960. In other words, the real fed funds rate turned from expansionary, at the onset, to contractionary, at the end of every recession. On the contrary, our estimates of r^* imply that the interest rate gap was indeed procyclical during most recession episodes. We obtain this result because, relative to DGGT, our estimates imply a smaller fall of the natural rate in the occurrence of recessions.

The DGGT estimates suggest that the countercyclical policy gap observed in recession periods was essentially caused by the Fed's neglect of the r_t^* endogeneity to liquidity shocks: the Taylor rules targeted the steady state value r^*, and discretionary monetary policy shocks did not correct for the bias of the policy rule. The historical decomposition of the policy gap has some implausible implications. For instance, according to DGGT and in contrast with our results, the sharp increase in real rates at the beginning of the 1980s was mainly determined by liquidity shocks and not by the well known Volcker disinflation. Further, and in contrast with several contributions (see Campbell et al. (2019) and references therein) and our model estimates, forward guidance shocks played almost no role in shaping the monetary policy stance after the Great Financial Crisis.

Summing up, the DGGT estimates suggest that the neglect of the r_t^* endogeneity to

[2]Specifically, the model developed by Laubach and Williams (2003), and its updated estimates, attribute a little more than 50% of the r^* decline since 1998 to the slowdown in trend growth, while the remaining fraction is imputed to other unspecified drivers.

[3]The impact demographic factors exert on r^* works (also) through shifts in saving and investment behaviors. Bean et al. (2015) distinguish these into shifts in propensity to save, propensity to invest, and demand for safe assets.

[4]We refer in particular to her comments on the "implausibly negative nominal r^*" obtained by DGGT.

liquidity shocks caused some apparently suboptimal policies, in line with Barsky et al. (2014). While there seems to be little doubt that targeting r^* is in principle desirable because it allows to incorporate additional information that is useful for the conduct of monetary policy, our results warn that shock misspecification might substantially bias estimates of r^*. Further, our estimates suggest that, even if the policy rule does not explicitly targets r^*, some apparently undesirable countercyclical features of the policy gap disappear when the set of observables allows to improve shock identification and estimates of r^*.

From a modeling perspective, we contribute to the DSGE literature that incorporates financial frictions. We combine the building blocks of the seminal works by Christiano et al. (2014) and Gertler and Karadi (2011), and we depart from the assumption of a single financial intermediary. Hirakata et al. (2011) and Suh and Walker (2016) also integrate financial frictions both at the entrepreneur and at the banking level, but they consider a unique financial intermediary. Somewhat closer to our NBFI specification, Durdu and Zhong (2021) build and estimate a model with bank and non-bank intermediaries; differently from our approach, their model features two types of entrepreneurs who distinctly borrow from banks or non-banks. In fact, our framework gives importance to the distinction between bank and non-bank credit (to the same firm), whose macroeconomic relevance has been underlined by De Fiore and Uhlig (2011), Becker and Ivashina (2014), and Herman et al. (2017) among the others.

We also contribute to the literature that investigates the counterfactual implications of liquidity shocks. Shi (2015) shows that an adverse liquidity shock in the spirit of Kiyotaki and Moore (2012) generates a counterfactual increase in equity prices. Attempts at addressing this issue include Cui and Radde (2019), who introduce costly financial intermediation, and Guerron-Quintana and Jinnai (2019), who eliminate the implausible rise in equity prices by adding to the model an endogenous growth mechanism that generates a persistent fall in dividends following the liquidity shock. The counterfactual implications of liquidity shocks uncovered in this paper cannot be solved in a similar way, simply because return spreads are not a by-product, but rather a necessary driver for the propagation of these shocks.

Finally, our finding that the post-2010 natural rate was consistently higher than in DGGT is in line with results in Kiley (2015) and Juselius et al. (2017), who estimate a higher r^* with respect to the Laubach and Williams (2003) benchmark, due to the inclusion of the financial cycle in the model and in the data used for estimation.[5]

The remainder of the paper is organized as follows. Section 2 describes the theoretical model that encompasses the DGGT and NBFI specifications. Section 3 introduces the estimation details and presents the empirical results. Section 4 concludes.

[5]Cukierman (2016) and Taylor and Wieland (2016) show theoretically how the omission of relevant variables, such as those characterizing the financial cycle, may cause a downward bias in the estimate of r^*. In a nutshell, by extending the Laubach and Williams (2003) model with additional variables, the output gap does not depend uniquely on the wedge between the actual and the natural rates. Hence, a strongly negative output gap does not necessarily have to correspond to a strongly negative r^*. While both papers formally make this argument for a semi-structural model, Taylor and Wieland (2016) suggest that the same mechanism should apply to a DSGE model.

2 Model

We build on the New York Fed DSGE model, which accounts for variable capacity utilization, indexation to past inflation in the price and wage Phillips curves,[6] and a time-varying inflation target in the Central Bank's monetary policy rule. Exogenous TFP dynamics incorporate both a stochastic trend and a trend-stationary component. Entrepreneurs borrow funds from financial intermediaries and their ability to turn raw physical capital into efficient capital units is subject to idiosyncratic efficiency (risk) shocks (see Christiano et al., 2014). Less efficient entrepreneurs will go bankrupt and the lenders will repossess the proceedings of the loan upon payment of a monitoring cost.[7] Expected returns from loans are therefore lower than the contractual lending rate.

The key innovation is that we allow for two alternative characterizations of the financial sector whose contribution to the model economy depends on the value assigned to the dummy α^{b^L}. When $\alpha^{b^L}=0$, the model replicates DGGT, *i.e* liquidity shocks drive a wedge between the riskless rate on T-bills and the bank deposit rate. When $\alpha^{b^L}=1$ (*NBFI* model henceforth), bank deposits and T-Bills are perfect substitutes in households' portfolios, *i.e* they equally provide liquidity services, and the model allows for non-bank financial intermediaries, broadly interpreted as investment funds that buy corporate bonds. In equilibrium, entrepreneurs treat bank and non-bank intermediaries as suppliers of homogeneous funds. By contrast, the liabilities of bank and non-bank intermediaries are imperfect substitutes in households' portfolios, because the latter do not provide liquidity services. Liquidity shocks, therefore, affect the spread between the two deposit rates. In what follows we provide the details of these alternative characterizations, whereas the full set of equilibrium conditions is described in Appendix 5.1.

2.1 Household portfolio choices

Household ι's expected lifetime utility is based on preferences defined over consumption, c_t, labor supply, L_t^h, and real holdings of a bundle of liquid assets, b_t^L:

$$E_0\sum_{t=0}^{\infty}\beta^t\left\{\left[\frac{(c_t(\iota)-\xi c_{t-1})^{1-\sigma_c}}{1-\sigma_c}\right]\exp\left(\frac{\sigma_c-1}{1+\nu_l}L_t^h(\iota)^{1+\nu_l}\right)+v_tU\left(b_t^L(\iota)\right)\right\}, \tag{1}$$

and v_t is a shock to the desire for liquidity.[8]

We posit that

$$b_t^L(\iota)=\frac{B_t(\iota)}{P_t}+\left(1+\frac{D_t^b(\iota)}{P_t}\right)^{\alpha^{b^L}}-1,$$

[6]The model adopts the Kimball aggregator in the intermediate goods and labor markets.

[7]Entrepreneurs are also constrained to use both loans and their own funds to buy physical capital.

[8]The treatment of the preference for liquidity strictly follows Fisher (2015), and we obviously assume that $U(\bullet)$ is positive, increasing, and concave.

where P_t is the price of consumption goods, B_t and D_t^b respectively define one-period nominal government bonds[9] and nominal bank deposits, and $\alpha^{b^L} = \{0,1\}$ identifies the (il)liquid status of bank deposits. Bank deposits and government bonds respectively yield the nominal rates $R_t^{d,b}$ and R_t, where the latter also is the *nominally* risk-free rate set by the Central Bank.

The flow budget constraint is

$$c_t(\iota) + \frac{B_t(\iota)}{R_t P_t} + \frac{D_t^b(\iota)}{R_t^{d,b} P_t} + \alpha^{b^L} \frac{D_t^{NBFI}(\iota)}{R_t^{d,NBFI} P_t} \leq \left(\frac{B_{t-1}(\iota)}{P_{t-1}} + \frac{D_{t-1}^b(\iota)}{P_{t-1}} + \alpha^{b^L} \frac{D_{t-1}^{NBFI}(\iota)}{P_{t-1}} \right) \frac{1}{\pi_t} + \\ + w_t L_t^h(\iota) - T_t(\iota) + \Pi_t(\iota), \tag{2}$$

where π_t is the inflation rate, w_t is the real wage, Π_t and T_t define the consumption value of dividends and lump-sum taxes, respectively. $D_t^{NBFI}(\iota)$ denote deposits held at a non-bank financial intermediary, which yields the nominal rate $R_t^{d,NBFI}$.

In the symmetrical equilibrium, the FOCs relevant for our analysis are:

$$\lambda_t = U'(c_t),$$

$$\lambda_t = v_t U'\left(b_t^L\right) + \beta E_t \left[\lambda_{t+1} \frac{R_t}{\pi_{t+1}} \right], \tag{3}$$

$$\lambda_t = \alpha^{b^L} \left[v_t U'\left(b_t^L\right) \right] \left(1 + \frac{D_t^b}{P_t} \right)^{\alpha^{b^L} - 1} + \beta E_t \left[\lambda_{t+1} \frac{R_t^{d,b}}{\pi_{t+1}} \right]. \tag{4}$$

When $\alpha^{b^L} = 0$, log-linearization yields

$$\hat{\lambda}_t = \hat{\varepsilon}_t^l + \hat{R}_t - E_t\left[\hat{\pi}_{t+1}\right] + E_t\left[\hat{\lambda}_{t+1}\right], \tag{5}$$

$$\hat{\lambda}_t = \hat{R}_t^{d,b} - E_t\left[\hat{\pi}_{t+1}\right] + E_t\left[\hat{\lambda}_{t+1}\right], \tag{6}$$

where $\hat{\varepsilon}_t^l = \lambda^{-1} U'(b^L) v_t$ is the normalized liquidity shock, which is assumed to follow an AR(1) process.[10] Note that:

$$\hat{R}_t^{d,b} = \hat{R}_t + \hat{\varepsilon}_t^l. \tag{7}$$

Thus, a positive liquidity shock inevitably raises the return on bank deposits above the monetary policy rate. Whilst this mechanism is left implicit in DGGT, Benigno and Nisticò (2017) propose a model with an analogous transmission for liquidity shocks.[11]

By contrast, when $\alpha^{b^L} = 1$ both assets provide liquidity services and

$$\hat{R}_t^{d,b} = \hat{R}_t.$$

[9] We will use “government bonds” interchangeably with “Treasuries” or “T-bills” to refer to B_t.

[10] Variables without the time subscript denote the respective steady-state values.

[11] Benigno and Nisticò (2017) explicitly depart from the literature, that for the most part studies shocks to credit spread between deposit and lending rates, to focus on a shock that raises the wedge between risk-free and deposit rates, the latter being less liquid than money. In their model, a liquidity shock additionally affects the proportion of deposits that can be transformed into money for consumption purchases.

Demand for D_t^{NBFI} is by assumption nil when $\alpha^{b^L} = 0$, whereas when $\alpha^{b^L} = 1$ it is driven by the standard Euler equation:

$$\lambda_t = \beta E_t \left[\lambda_{t+1} \frac{R_t^{d,NBFI}}{\pi_{t+1}} \right].$$

In this case, the liquidity shock drives a wedge between the return on deposits at the NBFI and the return on the two liquid assets, $\hat{R}_t$:

$$\hat{R}_t^{d,NBFI} = \hat{R}_t + \hat{\varepsilon}_t^l.$$

2.2 Entrepreneurs

In addition to his own resources, N_t^e, the representative entrepreneur borrows from financial intermediaries the funds, L_t, necessary to purchase from capital goods producers the physical capital, $\bar{k}_t$, at the market price Q_t:

$$Q_{t-1}\bar{k}_{t-1} = N_{t-1}^e + L_{t-1}.$$

Following Christiano et al. (2014), $\bar{k}_t$ is then transformed into effective capital conditionally to an idiosyncratic efficiency shock ω_t, and rented to intermediate goods producers at the nominal rental rate R_t^k. At the end of the period, the undepreciated capital is sold back to capital goods producers. Entrepreneurs' profits are

$$\Pi_t^e = \tilde{R}_t^k \omega_t Q_{t-1}\bar{k}_{t-1} - L_{t-1}R_t^{c,L}, \tag{8}$$

where $\tilde{R}_t^k$ is the gross nominal return to capital (that includes proceedings from selling undepreciated capital), and $R_t^{c,L}$ is the contractual lending rate. The combination of a predetermined lending rate with idiosyncratic productivity shocks exposes entrepreneurs to bankruptcy risk. In every period the productivity threshold $\overline{\omega}_t$ identifies the zero-profit condition that determines the fraction of bankrupt entrepreneurs, $F_t(\omega_t < \overline{\omega}_t)$. Note that banks repossess the assets of bankrupt entrepreneurs at the monitoring cost μ. In equilibrium, the following condition must hold:

$$[1 - F_t(\omega_t < \overline{\omega}_t)] L_{t-1}R_t^{c,L} + (1-\mu) \int_0^{\overline{\omega}_t} \tilde{R}_t^k \omega_t Q_{t-1}\bar{k}_{t-1} dF_t(\omega) = L_{t-1}R_t^L,$$

where R_t^L is the average return on loans.

2.3 Financial intermediaries

When $\alpha^{b^L} = 0$, we strictly follow DGGT, and perfectly competitive banks turn deposits into loans that earn the rate R_t^L. In this case,

$$R_t^{d,b} = R_t^L.$$

When $\alpha^{b^L} = 1$, both banks and non-bank intermediaries supply loans:

$$L_t = L_t^b + L_t^{NBFI}.$$

The structure of non-bank financial intermediaries is very simple. The representative *NBFI* is subject to the following technology:[12]

$$L_t^{NBFI} = \left(D_t^{NBFI}\right)^{\alpha_{NBFI}}, \ \alpha_{NBFI} < 1. \tag{9}$$

For any given average market return on loans, R_{t+1}^L, profit maximization yields the following supply condition for *NBFI* loans:

$$L_t^{NBFI} = \left(\frac{R_{t+1}^L}{R_t^{d,NBFI}}\right)^{\frac{\alpha_{NBFI}}{1-\alpha_{NBFI}}}. \tag{10}$$

Our modeling strategy for the banking sector follows Gertler and Karadi (2011). This financial friction implies that the endogenous spread on bank deposits is countercyclical, dampening the implausible surge in the supply of bank loans that would otherwise occur when liquidity shocks raise bank deposits. In a sense, this choice "stacks the cards" against our conjecture that liquidity shocks imply a counterfactual adjustment in the composition of firms' liabilities.

We posit that bankers may divert a fraction Λ of deposits. This, in turn, requires that bankers put skin in the game by accumulating their own net worth. Bankers exit the financial sector and become workers with probability $(1-\theta)$. Therefore, individual banking activity is expected to last $(1-\theta)^{-1}$ periods.[13] Exiting bankers transfer their net worth to households, who provide new bankers with an initial endowment corresponding to a fraction Ω of last-period loans, L_{t-1}^b. Bank loans amount to

$$L_t^b = \alpha^{b^L} N_t^b + D_t^b, \tag{11}$$

where N_t^b defines bankers' net worth. Bank profit maximization yields the following FOCs:

$$\nu_t = (1-\theta)\beta\frac{\lambda_{t+1}}{\lambda}\left(R_{t+1}^L - R_t^{d,b}\right) + \beta\theta\frac{\lambda_{t+1}}{\lambda_t} m_{t+1}\nu_{t+1}, \tag{12}$$

$$\eta_t = (1-\theta)\beta\frac{\lambda_{t+1}}{\lambda_t}R_t^{d,b} + \theta\beta\frac{\lambda_{t+1}}{\lambda_t}\zeta_{t+1}\eta_{t+1}, \tag{13}$$

$$\phi_t^b = \frac{\eta_t}{\Lambda - \nu_t}, \tag{14}$$

$$\zeta_t = (R_t^L - R_{t-1}^{d,b})\phi_{t-1}^b + R_{t-1}^{d,b}, \tag{15}$$

$$m_t = N_t^b / N_{t-1}^b = \frac{\phi_t^b}{\phi_{t-1}^b}\zeta_t, \tag{16}$$

$$N_t^b = \theta\zeta_t\varepsilon_t^{Nb}N_{t-1}^b + \Omega L_{t-1}^b. \tag{17}$$

ν_t and η_t respectively define the value to the banker of one additional unit of loans and net worth, ϕ_t^b is bank leverage, ζ_t is the growth rate of bank loans, and m_t is the growth rate of surviving bankers' net worth. ε_t^{Nb} is a shock that hits net worth accumulation as in Gertler and Karadi (2011) and follows an AR(1) process.

[12] In Mehra et al. (2011), returns to scale in the financial intermediation technology are constant, and the intermediation cost is a fixed proportion of loans. This, in turn, generates a fixed loan rate spread. Following their strategy here, where two financial intermediaries supply loans at the market rate, leads to model indeterminacy.

[13] This assumption is typically made to prevent bankers from accumulating net worth up to the point where they would no longer need deposits to supply loans.

3 Empirics

The first step in our empirical analysis is a straightforward replication of the estimates obtained in DGGT (*i.e.* $\alpha^{b^L} = 0$), which we take as a benchmark model, in order to discuss the implications of liquidity shocks for the smoothed series of the deposit rate. The second step is the estimation of the same empirical model *augmented* by the inclusion of one additional observable, *i.e.* a proxy for the commercial bank deposit rate. Finally, we depart from the DGGT benchmark and estimate the NBFI version of our model (*i.e.* $\alpha^{b^L} = 1$). As explained in detail below, our third estimation features two additional observables with respect to DGGT, specifically a measure of the non-bank deposit rate and the share of bank over total loans. All estimations are carried out with the `DSGE.jl` package available in Julia (Bezanson et al., 2017).

3.1 DGGT model

Following DGGT, the set of observables includes: real GDP and GDI growth for output, core PCE and GDP deflator for inflation, real consumption and investment growth, real wage growth, TFP growth, hours worked, fed funds rate, fed funds rate expectations up to 6 quarters ahead to account for the ZLB and forward guidance, 10-year Treasury yield, 10-year inflation expectations to account for a time-varying inflation target, spread between Aaa-rated corporate bonds and 20-year Treasury yields, spread between Baa-rated corporate bonds and 20-year Treasury yields. The estimation is carried out over the period 1960:I-2019:IV.[14] Data sources and transformation are presented in Appendix 5.4.

The model features a standard set of shocks and a few measurement errors.[15] The issue posed by the ZLB constraint is addressed by augmenting the monetary policy rule with anticipated (or news) shocks. This is combined with the inclusion of fed funds rate forecasts in the set of observables, so that the model's expectations for the policy rate match the market expectations. The liquidity shock is made up of a liquidity and a safety component, each of which is the sum of two AR(1) processes, meant to pick up highly persistent (with autoregressive coefficient fixed at 0.99) and transitory flight-to-quality episodes. In other words, there are actually four such shocks possibly hitting the economy: permanent liquidity, transitory liquidity, permanent safety, and transitory safety.

The presence of the two spreads among the observables is crucial to identify liquidity and safety shocks. Given their importance in this context, we report here the two related measurement equations while presenting the remaining ones in Appendix 5.3:

$$\text{Aaa - 20-year Treasury spread} = 100\ln(\varepsilon^{liq}) + E_t\left[\frac{1}{80}\sum_{j=0}^{79}\hat{\varepsilon}^{liq}_{t+j}\right] + e^{Aaa}_t, \tag{18}$$

$$\text{Baa - 20-year Treasury spread} = 100\ln\left(\varepsilon^{liq}\varepsilon^{safe}SP_*\right) + E_t\left[\frac{1}{80}\sum_{j=0}^{79}(\hat{\tilde{R}}^k_{t+j+1} - \hat{R}_{t+j})\right] + e^{Baa}_t. \tag{19}$$

The difference between Aaa-rated corporate bonds and Treasury yields is assumed to represent a liquidity premium. Specifically, it is mapped to the model as the sum of the steady-

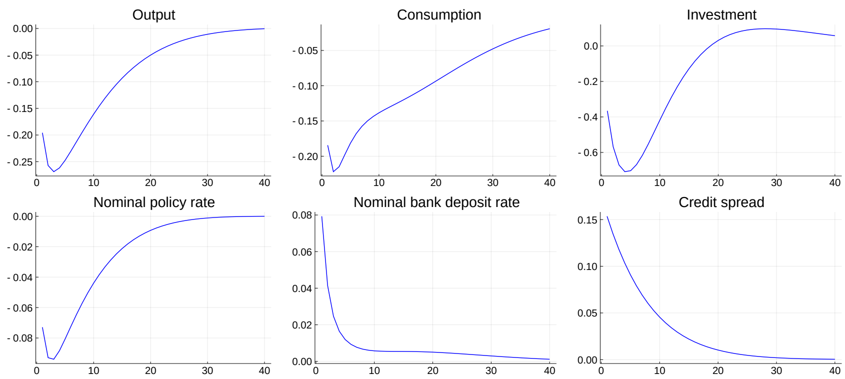
[14] Notice that we extend the estimation sample with respect to DGGT, who consider the period 1960:I-2016:III. All our findings hold irrespective of which of the two samples we use.

[15] The full list of shocks and measurement errors is presented in Appendix 5.2.

state liquidity premium ε^{liq}, the (expectations of future) liquidity shocks $\hat{\varepsilon}^{liq}_{t+j}$, and measurement error e^{Aaa}_t. Conversely, the spread between Baa-rated bonds and Treasury yields accounts for both safety and liquidity components, in addition to the default risk of entrepreneurs. The term in square brackets in (19) is the endogenous spread between the return on capital and the risk-free rate, where bank leverage, safety and liquidity shocks, and entrepreneur risk shocks enter. The observation equation is augmented with safety (ε^{safe}) and liquidity steady-state premia, an additional estimated spread SP_*, and measurement error e^{Baa}_t.

As the measurement equations show, the distinction between liquidity and safety shocks is purely "empirical", meaning that there is no endogenous difference between the two before taking the model to the data. Indeed, conditional on their standard deviation and autocorrelation being equal, liquidity and safety shocks will produce the same effects in all the model specifications we consider.

Figure 2: IRFs to an adverse transitory liquidity shock (DGGT)



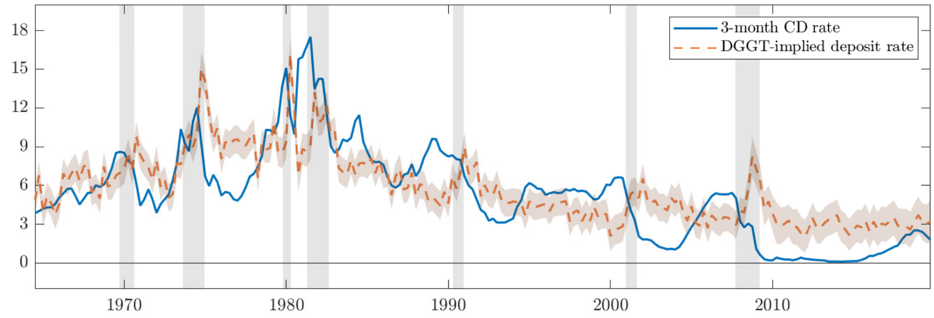
Note: Estimated impulse response functions at the posterior mode.

Figure 2 shows the estimated impulse response functions (IRFs henceforth) to a transitory liquidity shock. According to the flight-to-quality interpretation, households raise their demand for Treasuries, the deposit rate rises and so does the interest rate on loans, leading to a positive credit spread (*i.e.* a positive differential between lending and policy rates). The liquidity shock causes a slump in both consumption and investment.

Figure 3 plots the observed deposit rate against the smoothed series obtained from the benchmark estimation, which identifies liquidity shocks as one of the main drivers of business cycle fluctuations. As discussed in the introduction, the liquidity shock requires a divergence between deposit and policy rates which is unobservable over the sample period. In fact, the DGGT-implied deposit rate appears to be considerably more volatile than its proxy in the data.[16]

[16] Absent liquidity shocks, the model-implied deposit rate would be equal to the policy rate, and thus very close to its observed counterpart (see Figure 1, panel (a)).

Figure 3: Observed and model-implied bank deposit rate (DGGT)



Note: The dashed line is the posterior mean and the shaded area shows the 68% posterior coverage interval of the smoothed bank deposit rate (DGGT estimation). The solid line is the observed 3-month CD interest rate. 1964:III-2019:IV.

3.2 Augmented DGGT model

The augmented DGGT model (Augmented henceforth) is constrained to match one additional observable, *i.e.* a proxy for the banking sector deposit rate. Our series of choice is the secondary market rate on 3-month CDs, assets that match the 3-month maturity of T-bills whose return in the empirical model is proxied by the fed funds rate. The same measure is used by Hirakata et al. (2011) in the estimation of a DSGE model.[17]

The measurement equation for the deposit rate clarifies how this additional observable is going to discipline the estimate of liquidity shocks:

$$\begin{aligned} \text{3-month CD rate} &= 100(R^{d,b}-1)+\hat{R}_t^{d,b} \\ &= 100(R\varepsilon^{liq}\varepsilon^{safe}-1)+\hat{R}_t+\hat{\varepsilon}_t^{liq}+\hat{\varepsilon}_t^{safe}, \end{aligned} \tag{20}$$

where the second equality makes use of the deposit spread defined in (7), and $R^{d,b} = R\varepsilon^{liq}\varepsilon^{safe}$ is the implied steady-state deposit rate. Liquidity and safety shock now directly affect (and are identified by) the two corporate spreads and the wedge between the deposit and policy rates.

The CD rate time series is available from 1964:III to the end of the estimation sample and displays an average positive differential of 14 basis points over the fed funds rate. This raises the issue of matching the calibration of steady-state premiums chosen by DGGT. In their estimates, the deposit rate is an unobserved variable and they calibrate positive steady-state premiums for liquidity and safety that allow matching the average convenience yields found by Krishnamurthy and Vissing-Jorgensen (2012) for the Aaa- and the Baa-Treasury spreads. This calibration implicitly grants a steady-state spread for the deposit rate of 73 basis points over the risk-free policy rate and entails that it lies between the corresponding yields on Aaa and Baa corporate bonds. This is hard to reconcile with the observed average CD rate. To solve the problem, we have therefore chosen to demean both corporate-Treasury spreads and to remove steady-state safety and liquidity premiums ($\varepsilon^{liq} = \varepsilon^{safe} = 0$).

[17] Pesaran and Xu (2016) and Hollander and Liu (2016) consider the average between 1-, 3-, and 6-month secondary market CD rates. The differences between this average and the 3-month rate are in the order of basis-point decimals.

Existing alternatives to our proxy of the deposit rate would be characterized by lower average returns. For instance, Angeloni and Faia (2013) and Bekiros et al. (2018) consider the M2 own rate, a weighted average of the rates received on the interest-bearing assets included in M2. The M2 aggregate bundles assets of different maturities and its rate of return is characterized, on average, by a substantially *negative* differential with respect to the fed funds rate (around -2% between 1960:I and 2019:II, when the M2 own rate series was discontinued). An alternative measure is provided by Drechsler et al. (2017), who construct the average rate paid by commercial banks on savings deposits using U.S. Call Reports data from 1986:I to 2013:IV. Over this period, the savings deposit rate is on average 128 basis points lower than the fed funds rate.[18]

A full description of the prior distributions and the posterior estimates is left for the Appendix (Tables A1 and A2). With respect to the original DGGT specification, in all our estimations we impose a looser prior on the standard deviation of permanent safety and liquidity shocks. We discuss here the most significant differences between the Augmented and the DGGT posterior estimates.

The inverse of the elasticity of intertemporal substitution, σ_c, increases from 0.90 to 1.30. Given the non-separable preferences in consumption and leisure, this is sufficient to determine a shift from substitutability to complementarity between consumption and labor. As shown by Furlanetto and Seneca (2014), complementarity in consumption and labor is important to obtain procyclical consumption responses to MEI shocks.[19] Regarding the parameters determining internal persistence, the elasticity of investment adjustment costs, S'', is considerably larger and shifts from the lower to the upper end of the prior distribution, whereas the consumption habits parameter, h, falls from 0.49 to 0.21. In spite of the apparent anomaly relative to the benchmark, this is an intriguing result. In fact, empirical DSGE models obtain estimated values for the habit parameter that are at odds with microeconometric evidence (see Havranek et al., 2017). As per the parameters of the exogenous processes, *transitory* liquidity and safety shocks are less persistent and have a smaller standard deviation with respect to DGGT. On the other hand, the standard deviation of permanent flight-to-quality shocks remains fairly stable.[20]

The estimated IRFs to a liquidity shock are very close to those in Figure 2,[21] but the smoothed series obtained for the deposit rate obviously matches the corresponding observable we use to estimate the model. This, in turn, suggests that liquidity shocks might have a negligible impact on business cycle fluctuations.

Figure 4 shows the historical decomposition of GDP growth in the benchmark (panel (a)) and in the Augmented estimation (panel (b)) over the last twenty years of the sample. We focus on liquidity, productivity, MEI, risk, and monetary policy shocks. According to the DGGT model, the role of liquidity shocks was particularly pronounced in the last two recessions, whereas risk and MEI shocks played a lesser role. By contrast, the Augmented model proposes a quite different narrative: the importance of liquidity shocks is eroded in

[18]In Appendix 6, we discuss the estimates obtained when the M2 own rate and the savings deposit rate are chosen to proxy the model-implied bank deposit rate. We consider the alternative of imposing the DGGT steady-state calibration of the deposit rate, which implies that the estimated shocks are forced to match the gap with the observed average return on deposits. Our results are fully confirmed.

[19]Our posterior estimates do not violate the assumptions that consumption and leisure are non-inferior goods and that the utility function is concave (see Bilbiie, 2009, and Bilbiie, 2011).

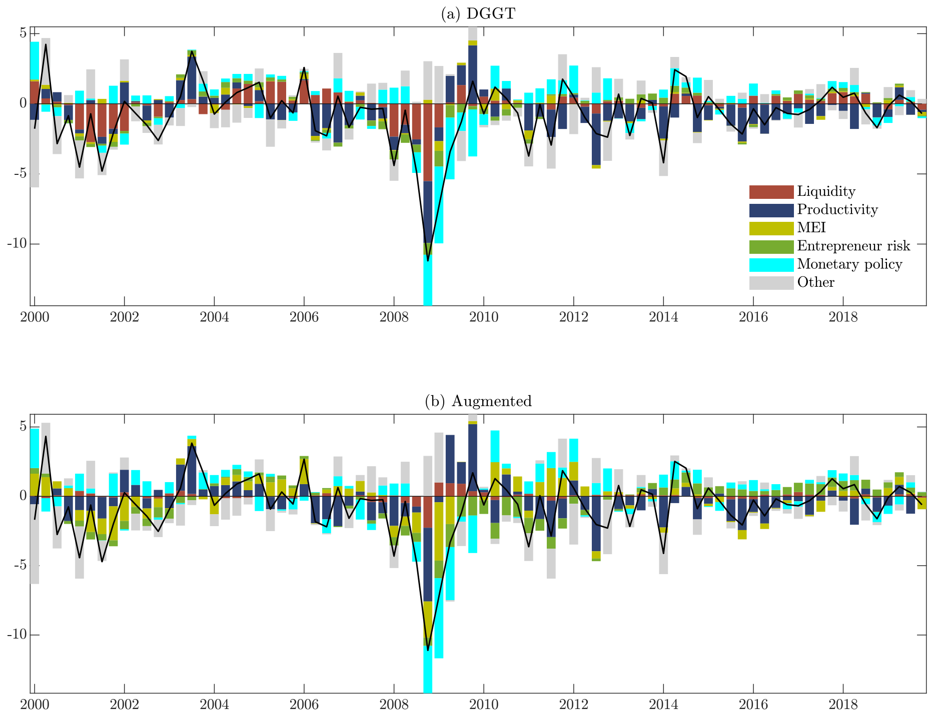
[20]We note in passing that our re-estimation of DGGT led to a substantial change in the MEI shock autocorrelation coefficient, which shifted from 0.96 in the original estimates to 0.24 in our results.

[21]Results available upon request.

favor of MEI and productivity shocks. Similar conclusions hold for the growth rates of consumption and investment, with the former (latter) most impacted by technology (MEI) shocks.[22]

Finally, it is interesting to note how the estimation handles the simultaneous observation of the two corporate spreads and the deposit rate, considering their relevance in identifying liquidity shocks. As evident from the Aaa-Treasury spread equation (18), the latter is determined only by liquidity shocks and measurement error: if the estimated standard deviation of liquidity shocks declines when adding the deposit rate, there is no other endogenous or exogenous variable that can make up for some of their effects on the Aaa-Treasury spread, beyond the measurement error itself. Indeed, the variance explained by the measurement error increases from 6% to 26% in the DGGT and Augmented estimations, respectively. Differently, the Baa-Treasury spread observation equation (19) contains a fully endogenous component in the excess return on capital, which is influenced by all structural shocks. In this respect, our Augmented estimation ends up relying less heavily on liquidity shocks, as expected, but also on measurement errors (whose contribution to the variance decomposition drops from 48% to 26% when the deposit rate is observed; see Table E1 in the

Figure 4: GDP growth historical shock decomposition (DGGT vs Augmented)



Note: Historical shock decomposition at the posterior mode. "Liquidity": sum of transitory liquidity, transitory safety, permanent liquidity, and permanent safety shocks; "Productivity": sum of stationary and permanent technology shocks; "Monetary policy": sum of contemporaneous and anticipated monetary policy shocks; "Other": sum of all other shocks and measurement errors, and initial values. 2000:I-2019:IV.

[22] See Table E1 in the Appendix for a variance decomposition analysis over the full sample and considering all shocks. The findings described above are confirmed. Table E1 also shows how DGGT attributes the largest part of the real policy rate's variation to liquidity shocks. Their role is nearly irrelevant in Augmented, and it is quite evenly replaced by technology, MEI, risk, and monetary policy shocks.

Appendix).

3.3 NBFI model

The NBFI model is built on the assumption that the return spread between bank deposits and T-bills is always nil, whereas liquidity shocks affect the spread between NBFI and commercial bank deposits. This, in turn, impacts on the share of bank loans out of total loans to firms. In this respect, liquidity shocks play an additional role that is absent in DGGT, which makes us consider the use of *two* supplementary observables in order to test their empirical plausibility.

Relative to the Augmented model, we replace our proxy for the banking sector deposit rate with a proxy for the deposit rate at NBFIs. Drawing from Krishnamurthy and Li (2022),[23] this is identified in the interest rate on 90-day P1-rated commercial paper (P1CP), whose data are available starting 1971:II. Since we do not take a stand on the precise nature of the non-bank intermediary, we insert a measurement error in the observation equation of the NBFI deposit rate, which otherwise mimics the bank deposit rate measurement equation (20). The set of observables also includes the growth rate of the ratio between commercial bank loans and total credit to the non-financial business sector. We construct this observable as in Becker and Ivashina (2014).[24] Following condition (17), we also estimate a shock to bankers' net worth accumulation, ε_t^{Nb}. As the P1CP rate is on average extremely close to the fed funds rate (the spread between the two series amounts to 1 basis point between 1971:II and 2019:IV), we follow the same strategy adopted in the Augmented case, *i.e.* we set steady-state safety and liquidity premiums at zero and demean the corporate spreads.

Before turning to the estimates, we briefly discuss the calibration of the parameters and steady-state values absent in the DGGT framework. Steady-state bank leverage, ϕ^b, and bankers' survival probability, θ, are set at 4 and 0.97156 respectively, as in Gertler and Karadi (2011). We calibrate the steady-state share of bank over total credit at 0.4, corresponding to the average ratio in the data used for estimation and consistent with De Fiore and Uhlig (2011). Lastly, we choose a value of 0.99 for the returns-to-scale coefficient in the NBFI intermediation technology, α_{NBFI}.[25]

Relative to the benchmark DGGT model, posterior estimates exhibit the following features. The (inverse) elasticity of intertemporal substitution, σ_c, is well above unity (1.42), the degree of consumption habits, h, is rather small (0.31), and S'', the elasticity of investment adjustment costs, is larger and close to its prior mean (4.06). These three estimates go in the same direction as in the Augmented case. Likewise, both (transitory) safety and liquidity shocks are less persistent and smaller in magnitude than in DGGT. Finally, wage markup shocks assume a high autocorrelation coefficient (0.88), as do shocks to bankers' net worth (0.95).

Impulse response functions to a liquidity shock are qualitatively similar to the ones estimated with the benchmark DGGT model, but the relative volatility induced by the shock is unambiguously limited in the NBFI model (see Figure 5).[26] In fact, the liquidity shock

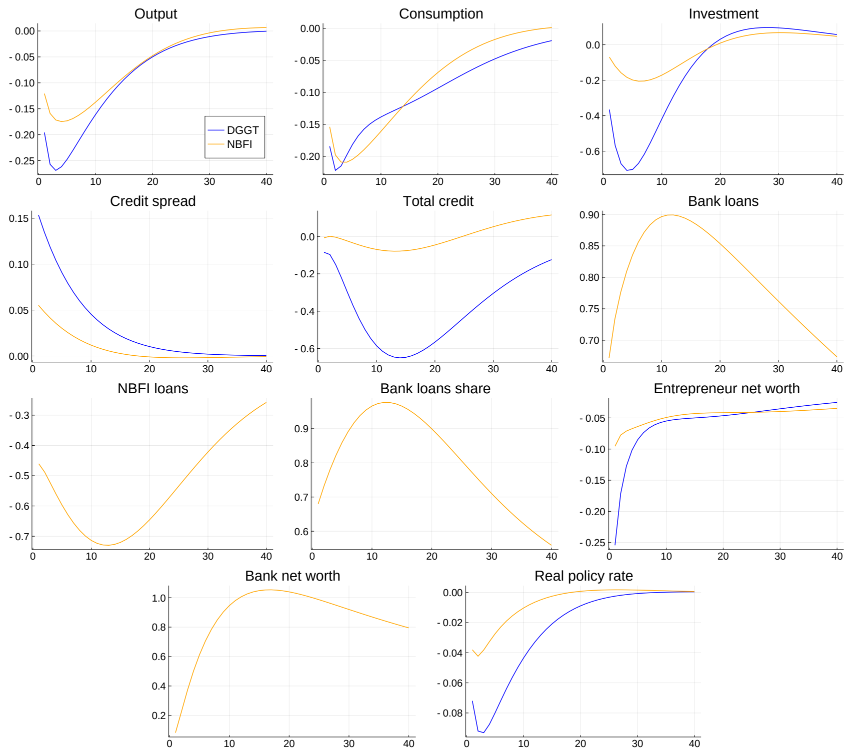
[23]Somewhat similarly to the present work, Krishnamurthy and Li (2022) consider a model with money (bank deposits), near-money (non-bank deposits), and Treasury bonds, where the three assets are allowed to differ in terms of substitutability and liquidity attributes.

[24]See Appendix 5.4 for a detailed description of how this and the other observables are constructed.

[25]We examine the calibration of α_{NBFI} and its implications in Appendix 7.

[26]For the sake of comparison, Figure 5 reproduces IRFs to a shock of the same standard deviation and

Figure 5: IRFs to an adverse transitory liquidity shock (DGGT vs NBFI)



Note: Estimated impulse response functions at the posterior mode.

induces households to accept a lower return on bank deposits, raising the bankers' continuation value. This, in turn, limits the credit spread and dampens the investment contraction. The IRFs also depict a marked and persistent increase in the share of bank loans and in banks' net worth. This casts doubts on the possibility that liquidity shocks play a major role in driving business cycle fluctuations: considering the whole sample, the correlation between the growth rates of the bank-credit share and GDP (investment) is 0.08 (0.23), similarly to Durdu and Zhong (2021), who find a weakly positive correlation of both bank and non-bank credit growth with real activity.[27]

In contrast with liquidity shocks, an adverse bank net worth shock produces a simultaneous fall in output and in the share of bank loans.[28] Following the shock, entrepreneurs turn to NBFIs, whose credit rises but not enough to offset the bank credit crunch, so that total lending persistently decreases. The drop in the real policy rate, though not immediate, insulates households' consumption that responds countercyclically. Importantly, the magnitude of the response is substantially larger for financial than for macroeconomic variables. This translates into a limited influence of bank net worth shocks in the shock decomposition of the main macro aggregates.

IRFs to the remaining shocks are similar across the DGGT and NBFI estimates, with one important exception. The response of consumption to a MEI shock turns from counter-

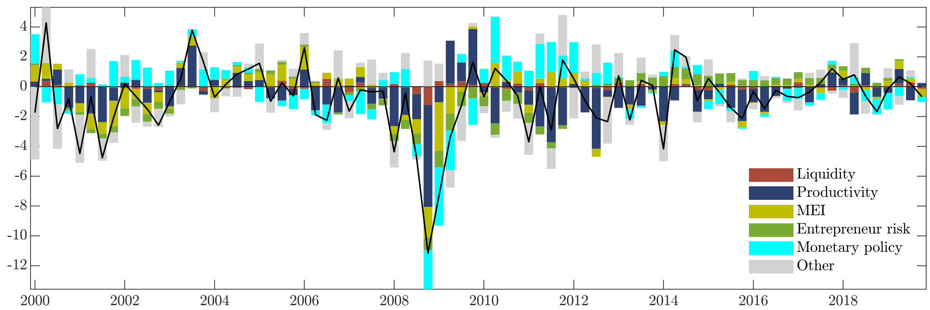
persistence. Specifically, we choose the DGGT estimates.

[27] Durdu and Zhong (2021) consider a different sample (1987:I-2015:I) and a different dataset, which they build tracing credit through intermediation chains that depart from non-financial corporate borrowers.

[28] See Figure E1 in the Appendix.

cyclical to procyclical in the NBFI model,[29] thanks to the shift in the estimated elasticity of intertemporal substitution that grants complementarity between consumption and labor. Conversely, consumption still reacts positively to an adverse entrepreneur risk shock in NBFI,[30] thus replicating the pattern observed for the bank net worth shock. In fact, both MEI and financial-friction shocks have often been recognized in the literature for not being able to generate a positive co-movement between investment and consumption (see for instance Furlanetto and Seneca, 2014, and Suh and Walker, 2016).

Figure 6: GDP growth historical shock decomposition (NBFI)



Note: Historical shock decomposition at the posterior mode. "Liquidity": sum of transitory liquidity, transitory safety, permanent liquidity, and permanent safety shocks; "Productivity": sum of stationary and permanent technology shocks; "Monetary policy": sum of contemporaneous and anticipated monetary policy shocks; "Other": sum of all other shocks and measurement errors, and initial values. 2000:I-2019:IV.

Figure 6 reports GDP growth historical decomposition according to the NBFI model. Even during the global financial crisis, liquidity shocks are barely noticeable and play no role in other periods. MEI shocks assume higher relevance especially between 2008 and 2010, confirming the results obtained with the Augmented estimation.[31] As for the observed credit spreads, our NBFI model does a poorer job of matching the Aaa- and Baa-Treasury spreads, whose variance explained by measurement errors significantly increases with respect to both the DGGT and Augmented estimates (as shown in Table E1 in the Appendix).

To conclude this discussion, we describe how the estimates of NBFI change when we remove the P1CP rate from the set of observables. This exercise is helpful for understanding where the "constraints" on the potential role of liquidity shocks come from. Under this alternative specification, the liquidity shock makes a comeback (albeit less pervasively

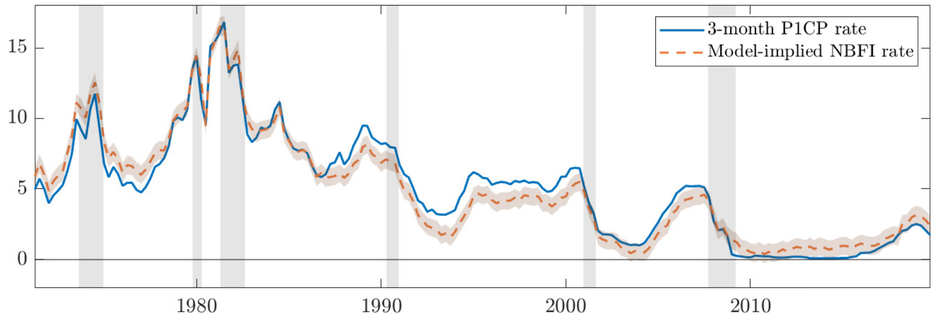
[29]See Figure E2 in the Appendix.

[30]See Figure E3 in the Appendix.

[31]Table E1 in the Appendix further demonstrates the consistency between Augmented and NBFI estimates in terms of variance decomposition. The two models draw a slightly different picture for the determinants of the real policy rate: according to NBFI, this was less affected by MEI and risk shocks, and more influenced by productivity and monetary policy.

than in DGGT) because the empirical model is not forced to replicate the dynamics observed for the NBFI deposit rate.[32] In fact, a gap opens up between the observed and the model-implied NBFI deposit rate (see Figure 7). Interestingly, the mismatch of the non-bank deposit rate is much less pronounced with respect to the bank deposit rate in DGGT. Including the bank-loans share in the observables apparently alleviates the counterfactual implications of liquidity shocks.

Figure 7: Observed and model-implied NBFI deposit rate (NBFI, P1CP rate not observed)



Note: The dashed line is the posterior mean and the shaded area shows the 68% posterior coverage interval from the alternative NBFI estimation (with bank-loans-share growth as the unique additional observable). The solid line is the observed 3-month P1CP interest rate. 1971:II-2019:IV

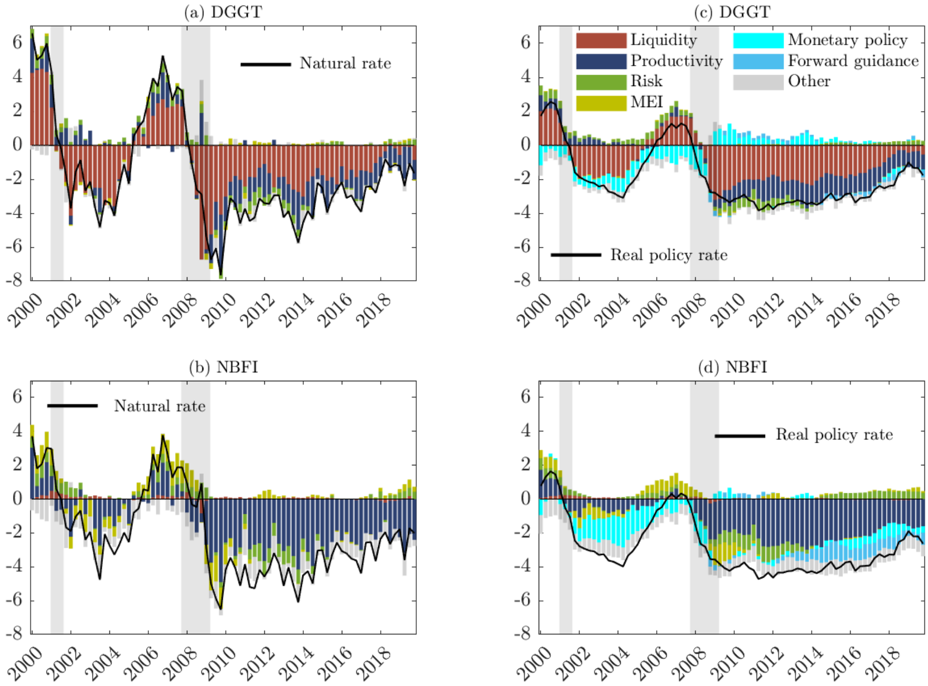
3.4 The natural rate and the Fed monetary policy stance. A reinterpretation

There are some interesting insights from the historical decomposition of the natural interest rate, *i.e.* the risk-free rate estimated when prices and nominal wages are flexible and markup shocks are assumed away. Liquidity shocks have a one-for-one impact on the natural rate: to fully absorb an adverse liquidity shock, the real interest rate should adjust by a magnitude such that the households' incentive to turn to liquid assets is neutralized. This is exactly what happens under flexible prices, explaining why r^* falls one-for-one. Panels (a) and (b) of Figure 8 report the historical decomposition of the natural rate estimates obtained from the DGGT and NBFI models.

According to the DGGT model, liquidity shocks are responsible for the post-2000 persistent fall in r^*. The NBFI estimates tell a quite different story: liquidity shocks did not matter, and the natural rate decline is instead mainly attributed to a slowdown in productivity growth. Panels (c) and (d) show the historical decomposition of the observed real policy rates. These are obviously co-determined by nominal frictions and react to the full set of shocks. The two decompositions "inherit" the drastically different role of liquidity shocks

[32] See Figure D1, panel (a), in the Appendix for the historical decomposition of GDP growth. Appendix 8 reports a detailed discussion of this alternative NBFI estimation.

Figure 8: Real policy and natural rates historical shock decomposition (DGGT vs NBFI)



Note: Historical shock decomposition at the posterior mode. “Liquidity”: sum of transitory liquidity, transitory safety, permanent liquidity, and permanent safety shocks; “Productivity”: sum of stationary and permanent technology shocks; “Monetary policy”: contemporaneous monetary policy shocks; “Forward guidance”: sum of anticipated monetary policy shocks; “Other”: sum of all other shocks and measurement errors, and initial values. 2000:I-2019:IV.

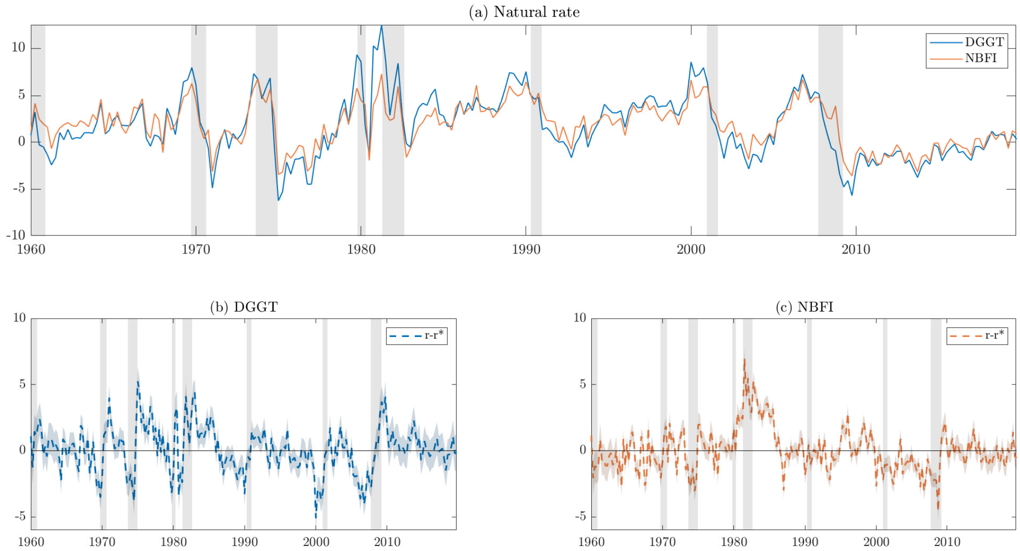
in determining the two r^* estimates. Further, the DGGT and NBFI estimates crucially differ in the role assigned to monetary policy shocks. According to DGGT, policy shocks were mildly expansionary between 2000 and 2009 and turned mildly contractionary thereafter. According to NBFI estimates, monetary shocks played an important role in depressing the policy rate between 2002 and 2006, in line with the Great Deviation view (Taylor, 2007, 2011), and were also markedly expansionary after 2013. Over this period, most of the monetary easing comes from forward guidance shocks, while these latter effects are virtually absent in DGGT estimates.

The two models have different implications for the estimated volatilities of r^*. Figure 9, panel (a), shows that DGGT predicts a larger volatility of the natural rate: at the posterior mode, the standard deviation of r^* in NBFI is 28% smaller than in DGGT, and this is almost entirely due to the different contribution of estimated liquidity shocks.

Both models predict that r^* is relatively high towards the end of an expansionary phase before abruptly falling during the recession, but the DGGT model systematically estimates a stronger contraction with respect to NBFI. Panels (b) and (c) of Figure 9 report the estimated cyclical patterns of the interest rate gap. From a Wicksellian perspective, it is the gap between the actual and the natural interest rate that matters for determining the former’s stabilizing role, rather than the value of the policy rate itself.

According to DGGT, a countercyclical gap exists between the policy rate and r^*: this

Figure 9: Natural rates and policy rate gaps (DGGT vs NBFI)



Note: Panel (a): smoothed estimate of r^* at the posterior mode. Panels (b) and (c): smoothed estimate of the interest rate gap (*i.e.* real policy rate minus natural rate); the dashed line is the posterior mean and the shaded area shows the 68% posterior coverage interval. 1960:I-2019:IV.

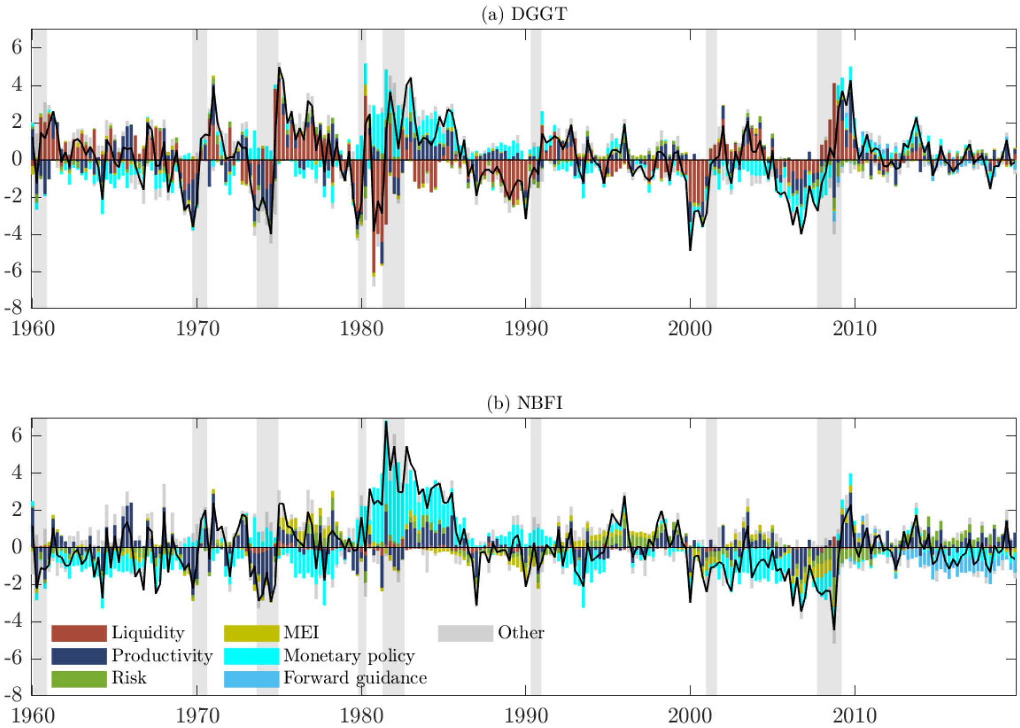
gap typically reaches a minimum before the onset of every recession and is consistently increasing thereafter, suggesting strong swings in the monetary policy stance that turns from accommodative to restrictive during the recessionary episode. By contrast, NBFI estimates suggest that, at least since 1981, the gap reaches the maximum at the onset of the recession, and falls afterward.

In Figure 10 we report the historical decompositions of the $r - r^*$ gaps estimated under the two models. According to the DGGT model, the policy gap is almost entirely explained by liquidity and monetary policy shocks. The former are virtually absent in the NBFI estimates, and monetary policy shocks play a much larger role. In a nutshell, the DGGT estimates suggest that the countercyclical policy gap observed in recession periods was essentially caused by the Fed's neglect of the r_t^* endogeneity to liquidity shocks: the Taylor rules targeted the steady state value r^*, and discretionary monetary policy shocks did not correct for the bias of the policy rule.

Specific episodes are quite instructive about the different implications of the two models. Consider the well known disinflationary episode of the early 1980s. According to popular wisdom (Goodfriend and King (2005); Bordo et al. (2007)) it was the consequence of a "surprise" U-turn in the monetary policy stance. In fact, the DGGT model predicts a sharp increase in the natural rate just at the beginning of the 1980s, when $r^* > 10\%$ reaches the maximum of the sample (see Figure 9). For this reason, the DGGT model downplays the increase in the policy gap, which is even negative in 1981, and becomes consistently positive after the end of the recessionary episode. In consequence of this, the historical decomposition of $r - r^*$ assigns a limited role to monetary policy shocks. By contrast, the NBFI model provides a more conventional interpretation of the disinflation, where monetary policy shocks cause a large and increasing policy gap, which reaches the maximum right at the onset of the 1981-1982 recession.

The $r - r^*$ gaps estimated for the financial crisis episode are also illuminating: accord-

Figure 10: Policy rate gap historical shock decomposition (DGGT vs NBFI)



Note: Historical shock decomposition at the posterior mode. "Liquidity": sum of transitory liquidity, transitory safety, permanent liquidity, and permanent safety shocks; "Productivity": sum of stationary and permanent technology shocks; "Monetary policy": contemporaneous monetary policy shocks; "Forward guidance": sum of anticipated monetary policy shocks; "Other": sum of all other shocks and measurement errors, and initial values. 2000:I-2019:IV.

ing to DGGT, the gap was strongly negative in 2007, then gradually increased to become strongly positive in 2009, when the recovery began. According to NBFI, the monetary stance was almost neutral in 2007 and turned strongly expansionary during the crisis period. Crucially, given that the real policy rate is an observed variable, the opposite patterns in the $r - r^*$ gaps are entirely determined by the different estimates the two models generate for r^*. Figure 10 also shows that, according to DGGT, interest rate shocks where mainly contractionary immediately after the Great Recession, possibly due to the ZLB binding constraint, and forward guidance shocks played almost no role in shaping the monetary policy stance. By contrast, the NBFI estimates suggest that interest rate shocks were mainly expansionary after 2009, and forward guidance shocks did matter for the $r - r^*$ gap.

4 Conclusions

We build a business cycle model that encompasses two alternative characterizations of financial markets: a standard one, with a single financial intermediary; and a more complex one, where bank and non-bank intermediaries coexist. In both cases, we shed light on the counterfactual implications liquidity shocks have for deposit rates and for the portfolio composition of firms' liabilities. Once we extend the standard set of observables with the relevant financial variables, we find that liquidity shocks did not play a significant role in the U.S. business cycle.

Further, our estimates are less pessimistic about the fall of the natural interest rate and do not support the popular view that it is explained by flight-to-liquidity shocks. In this regard, we identify the slowdown in productivity growth as the main responsible.

We are also more sanguine about the conduct of monetary policy, as we find that the interest rate gap (i.e. the wedge between the real policy rate and r^*) was procyclical in occasion of most recession episodes, thus indicating an expansionary monetary policy stance during these periods. With reference to the post-GFC crisis, and in contrast with the DGGT model, we obtain that interest rate shocks where mainly expansionary and forward guidance did play a role in stimulating the US economy.

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Online appendix

5 Empirical model

5.1 Model description

As mentioned in Section 2, we estimate the DGGT version of the New York Fed DSGE model and an enhanced version of it that adds non-bank financial intermediaries and Gertler and Karadi (2011) frictions to the banking sector. We refer the reader to DGGT online appendix for a comprehensive description of their model, while the present section is limited to the specification of growth in the model economy and to a list of the log-linearized equilibrium conditions.

Growth is exogenous and driven by the technology process Z_t^*, defined as

$$Z_t^* = e^{\frac{1}{1-\alpha}\tilde{z}_t} Z_t^p e^{\gamma t},$$

which includes a stochastic trend (Z_t^p), a deterministic trend (γ), and a stationary component ($\tilde{z}_t$). $\tilde{z}_t$ and the growth rate of Z_t^p follow an AR(1) process.

5.1.1 Equations common to DGGT and NBFI[33]

- Household marginal utility of consumption:

$$\hat{c}_t = he^{-z^*}(\hat{c}_{t-1} - \hat{z}_t^*) - \frac{1-he^{-z^*}}{\sigma_c}\hat{\tilde{\lambda}}_t + \frac{\sigma_c - 1}{\sigma_c}\frac{wL^h}{c}\hat{L}_t^h, \tag{1.A1}$$

  where $z_t^* = \frac{Z_t^*}{Z_{t-1}^*}$ is the stochastic growth rate of the economy and $\tilde{\lambda}_t$ is transformed marginal utility of consumption ($\lambda_t = \tilde{\lambda}_t (Z_t^*)^{-\sigma_c}$).

- Household liquid asset Euler equation:

$$\hat{\tilde{\lambda}}_t = \hat{\tilde{\lambda}}_{t+1} + \hat{R}_t - E_t[\hat{\pi}_{t+1}] + \hat{\varepsilon}_t^l - \sigma_c E_t[\hat{z}_{t+1}^*]. \tag{1.A2}$$

- Optimal investment decision:

$$\hat{i}_t = \frac{\hat{q}_t}{S'' e^{2z^*}(1+\tilde{\beta})} + \frac{1}{1+\tilde{\beta}}(\hat{i}_{t-1} - \hat{z}_t^*) + \frac{\tilde{\beta}}{1+\tilde{\beta}}E_t[\hat{i}_{t+1} + \hat{z}_{t+1}^*] + \hat{\mu}_t, \tag{1.A3}$$

  where $\tilde{\beta} = \beta e^{(1-\sigma_c)z^*}$ and $\hat{\mu}_t$ is a shock to the marginal efficiency of investment (MEI) that follows an AR(1) process.

- Optimal rate of capital utilization:

$$\hat{u}_t = \frac{1-\psi}{\psi}\hat{r}_t^k. \tag{1.A4}$$

[33] We use the following notation: for a given variable x_t, $\hat{x}_t$ and x respectively represent its log-deviation from the steady state and its steady-state value.

- Effective capital:

$$\hat{k}_t = \hat{\bar{k}}_{t-1} + \hat{u}_t - \hat{z}^*_t. \tag{1.A5}$$

- Entrepreneur nominal return to capital:

$$\hat{\tilde{R}}^k_t = \frac{r^k}{r^k + 1 - \delta} \hat{r}^k_t + \frac{1 - \delta}{r^k + 1 - \delta} \hat{q}_t - \hat{q}_{t-1} + \hat{\pi}_t. \tag{1.A6}$$

- Entrepreneur excess return on capital (*i.e.* spread between expected return on capital and borrowing rate for entrepreneurs):

$$E_t[\hat{\tilde{R}}^k_{t+1} - \hat{R}^L_t] = \zeta_{sp,b}(\hat{q}_t + \hat{\bar{k}}_t - \hat{n}^e_t) + \hat{\tilde{\sigma}}_{\omega,t}, \tag{1.A7}$$

  where $\hat{\tilde{\sigma}}_{\omega,t}$ is a shock to the riskiness of entrepreneurs (risk) that follows an AR(1) process.

- Entrepreneur net worth evolution:

$$\begin{aligned}\hat{n}^e_t = \zeta_{n^e,\tilde{R}^k} \left(\hat{\tilde{R}}^k_t - \hat{\pi}_t\right) - \zeta_{n^e,R} \left(\hat{R}^L_{t-1} - \hat{\pi}_t\right) + \zeta_{n^e,qK}(\hat{q}_{t-1} + \hat{\bar{k}}_{t-1}) + \\ + \zeta_{n^e,n^e}\hat{n}^e_{t-1} - \gamma_* \frac{v}{n^e} \hat{z}^*_t - \frac{\zeta_{n,\sigma_\omega}}{\zeta_{sp,\sigma_\omega}} \hat{\tilde{\sigma}}_{\omega,t-1},\end{aligned} \tag{1.A8}$$

  where the ζ terms are steady-state elasticities, v is steady-state entrepreneur equity, and γ_* is the fraction of surviving entrepreneurs.

- Production function:

$$\hat{y}_t = \Phi \left[\alpha \hat{k}_t + (1-\alpha)\hat{L}^h_t\right]. \tag{1.A9}$$

- Capital evolution:

$$\hat{\bar{k}}_t = \left(1 - \frac{i}{\bar{k}}\right) \left(\hat{\bar{k}}_{t-1} - \hat{z}^*_t\right) + \frac{i}{\bar{k}} \hat{i}_t + \frac{i}{\bar{k}} S'' e^{2z^*}(1+\tilde{\beta})\hat{\mu}_t. \tag{1.A10}$$

- Real rental rate of capital:

$$\hat{r}^k_t = \hat{L}^h_t + \hat{w}_t - \hat{k}_t. \tag{1.A11}$$

- Real marginal costs:

$$\widehat{mc}_t = \hat{w}_t + \alpha \left(\hat{L}^h_t - \hat{k}_t\right). \tag{1.A12}$$

- Marginal rate of substitution between consumption and labor:

$$\hat{\mu}_{w,t} = \hat{w}_t - \nu_l \hat{L}^h_t - \frac{1}{1 - he^{-z^*}} \hat{c}_t + \frac{he^{-z^*}}{1 - he^{-z^*}} (\hat{c}_{t-1} - \hat{z}^*_t). \tag{1.A13}$$

- Price Phillips curve:

$$\hat{\pi}_t = \frac{\iota_p}{1 + \iota_p \tilde{\beta}} \hat{\pi}_{t-1} + \frac{\tilde{\beta}}{1 + \iota_p \tilde{\beta}} E_t[\hat{\pi}_{t+1}] + \frac{(1 - \zeta_p \tilde{\beta})(1 - \zeta_p)}{\zeta_p [(\Phi - 1)\varepsilon_p + 1](1 + \iota_p \tilde{\beta})} \widehat{mc}_t + \hat{\lambda}_{p,t}, \tag{1.A14}$$

  where $\hat{\lambda}_{p,t}$ is a price markup shock that follows an ARMA(1,1) process.

- Wage Phillips curve:

$$w_t = -\frac{(1-\zeta_w\tilde{\beta})(1-\zeta_w)}{\zeta_w\left[(\lambda_w-1)\varepsilon_w+1\right](1+\tilde{\beta})}\hat{\mu}_{w,t} + \frac{1}{1+\tilde{\beta}}(\hat{w}_{t-1}-\hat{z}^*_t+\iota_w\hat{\pi}_{t-1}) - \frac{1+\iota_w\tilde{\beta}}{1+\tilde{\beta}}\hat{\pi}_t + \\ + \frac{\tilde{\beta}}{1+\tilde{\beta}}E_t[\hat{w}_{t+1}+\hat{\pi}_{t+1}+\hat{z}^*_{t+1}] + \hat{\lambda}_{w,t}, \tag{1.A15}$$

where $\hat{\lambda}_{w,t}$ is a wage markup shock that follows an ARMA(1,1) process.

- Aggregate resource constraint:

$$\hat{y}_t = \frac{c}{i}\hat{c}_t + \frac{i}{y}\hat{i}_t + r^k\frac{k}{y}\hat{u}_t + g_*\hat{g}_t, \tag{1.A16}$$

where exogenous government spending is defined as $\hat{g}_t = log\left(\frac{G_t}{Z^*_t y g_*}\right)$ and follows an AR(1) process (the shock is allowed to be correlated with stationary technology innovations).

- Monetary policy rule:

$$\hat{R}_t = \rho_R\hat{R}_{t-1} + (1-\rho_R)\left[\psi_1(\hat{\pi}_t-\pi^*_t)+\psi_2(\hat{y}_t-\hat{y}^f_t)\right] + \psi_3\left[(\hat{y}_t-\hat{y}^f_t)-(\hat{y}_{t-1}-\hat{y}^f_{t-1})\right] + \hat{r}^m_t, \tag{1.A17}$$

where $\hat{y}^f_t$ is output in the flexible-price economy, $\hat{\pi}^*_t$ is a stochastic inflation target (that follows an AR(1) process), and $\hat{r}^m_t$ is a monetary policy shock. The latter evolves as follows:

$$\hat{r}^m_t = \rho_{r^m}\hat{r}^m_{t-1} + \varepsilon^R_t + \sum_{k=1}^{K}\varepsilon^R_{k,t-k}, \tag{1.A18}$$

where ε^R_t is the standard contemporaneous shock, whereas $\varepsilon^R_{k,t-k}$ is a shock that is known to agents at time $t-k$ but takes effect in time t: thus, it can be interpreted as a forward guidance shock in that it anticipates future policy decisions by k quarters.

- The DGGT model is closed by the following condition (that derives from the household illiquid asset Euler equation):

$$\hat{R}^L_t = \hat{R}^{d,b}_t = \hat{R}_t + \hat{\varepsilon}^l_t. \tag{1.A19}$$

5.1.2 Equations specific to NBFI

- Equation (1.A19) is replaced by

$$\hat{R}^{d,b}_t = \hat{R}_t, \tag{1.A20}$$

$$\hat{R}^{d,NBFI}_t = \hat{R}_t + \hat{\varepsilon}^l_t. \tag{1.A21}$$

- NBFI (and bank) lending rate:

$$\hat{R}^L_t = \hat{R}^{d,NBFI}_t + (1-\alpha_{NBFI})\hat{d}^{NBFI}_t. \tag{1.A22}$$

- NBFI loan supply:

$$\hat{l}_t^{NBFI} = \alpha_{NBFI}\hat{d}_t^{NBFI}. \tag{1.A23}$$

- Bank loan supply:

$$\hat{l}_t^b = \hat{\phi}_t^b + \hat{n}_t^b. \tag{1.A24}$$

- Value of bank capital:

$$\hat{v}_t = \tilde{\beta}\left[\frac{1-\theta}{v}(R^L - R) + \theta m\right] E_t\left[\hat{\tilde{\lambda}}_{t+1} - \hat{\tilde{\lambda}}_t - \sigma_c \hat{z}_{t+1}^*\right] + \frac{1-\theta}{v}\tilde{\beta}E_t\left[R^L\hat{R}_{t+1}^L - R\hat{R}_t^{d,b}\right] + \\ + \theta\tilde{\beta}mE_t\left[\hat{m}_{t+1} + \hat{v}_{t+1}\right]. \tag{1.A25}$$

- Value of bank net worth:

$$\hat{\eta}_t = E_t\left[\hat{\tilde{\lambda}}_{t+1} - \sigma_c \hat{z}_{t+1}^*\right] - \hat{\tilde{\lambda}}_t + \left(1 - \theta\tilde{\beta}\zeta\right)\hat{R}_t^{d,b} + \theta\tilde{\beta}\zeta E_t\left[\hat{\zeta}_{t+1} + \hat{\eta}_{t+1}\right]. \tag{1.A26}$$

- Bank optimal leverage:

$$\hat{\phi}_t^b = \hat{\eta}_t + \frac{v}{\Lambda - v}\hat{v}_t. \tag{1.A27}$$

- Growth rate of bank capital:

$$\zeta\hat{\zeta}_t = R^L\phi^b\hat{R}_t^L + (R^L - R)\phi^b\hat{\phi}_{t-1}^b + R(1-\phi^b)\hat{R}_{t-1}^d. \tag{1.A28}$$

- Growth rate of bank net worth:

$$\hat{m}_t = \hat{\zeta}_t + \hat{\phi}_t^b - \hat{\phi}_{t-1}^b. \tag{1.A29}$$

- Bank net worth evolution:

$$\hat{n}_t^b = \theta\zeta e^{-z^*}\left(\hat{\zeta}_t - \hat{z}_t^* + \hat{n}_{t-1}^b + \hat{\varepsilon}_t^{Nb}\right) + \Omega\phi^b\hat{l}_t^b. \tag{1.A30}$$

- Total loan supply:

$$\hat{l}_t = \frac{l^b}{l}\hat{l}_t^b + \frac{1-l^b}{l}\hat{l}_t^{NBFI}. \tag{1.A31}$$

- Entrepreneur balance sheet:

$$\hat{q}_t + \hat{\bar{k}}_t = \frac{1-n^e}{\bar{k}}\hat{l}_t + \frac{n^e}{\bar{k}}\hat{n}_t^e. \tag{1.A32}$$

- Share of bank loans over total credit:

$$\hat{l}_t^{b,share} = \hat{l}_t^b - \hat{l}_t. \tag{1.A33}$$

5.2 Shocks and measurement errors

The model is characterized by the following structural shocks: stationary technology shock and shock to the growth rate of technology; liquidity shock; MEI shock; risk shock; wage and price markup shock; government spending shock; inflation target shock; contemporaneous monetary policy shock; anticipated monetary policy shocks up to six quarters ahead; bank net worth shock (only for the NBFI specification).

The flight-to-quality shock appearing in equilibrium conditions (1.A2), (1.A19), and (1.A21), $\hat{\varepsilon}_t^l$, is defined as the sum of safety and liquidity shocks:

$$\hat{\varepsilon}_t^l = \hat{\varepsilon}_t^{safe} + \hat{\varepsilon}_t^{liq},$$

where the first term is the sum of transitory and permanent safety shocks, namely $\hat{\varepsilon}_t^{safe,T}$ and $\hat{\varepsilon}_t^{safe,P}$, and the second is the sum of transitory and permanent liquidity shocks, $\hat{\varepsilon}_t^{liq,T}$ and $\hat{\varepsilon}_t^{liq,P}$. All four shocks follow AR(1) processes.

In addition to the structural shocks, measurement errors, denoted by e_t, are assumed for a subset of the observables. These include output growth (with two distinct errors on GDP and GDI growth), inflation (with two distinct errors on core PCE inflation and GDP deflator inflation), the 10-year Treasury yield, TFP growth, the Aaa- and Baa-Treasury spreads, and the NBFI deposit rate (only for the NBFI specification).

5.3 Measurement equations

$$\begin{aligned}
\text{GDP growth} &= 100\gamma + (\hat{y}_t - \hat{y}_{t-1} + \hat{z}_t^*) + e_t^{gdp} - e_{t-1}^{gdp} \\
\text{GDI growth} &= 100\gamma + (\hat{y}_t - \hat{y}_{t-1} + \hat{z}_t^*) + e_t^{gdi} - e_{t-1}^{gdi} \\
\text{Consumption growth} &= 100\gamma + (\hat{c}_t - \hat{c}_{t-1} + \hat{z}_t^*) \\
\text{Investment growth} &= 100\gamma + (\hat{\imath}_t - \hat{\imath}_{t-1} + \hat{z}_t^*) \\
\text{Real wage growth} &= 100\gamma + (\hat{w}_t - \hat{w}_{t-1} + \hat{z}_t^*) \\
\text{Hours} &= \bar{L} + \hat{L}_t^h \\
\text{Core PCE inflation} &= 100(\pi - 1) + \hat{\pi}_t + e_t^{pce} \\
\text{GDP deflator inflation} &= 100(\pi - 1) + \delta_{gdpdef} + \gamma_{gdpdef}\hat{\pi}_t + e_t^{gdpdef} \\
\text{Fed funds rate} &= 100(R - 1) + \hat{R}_t \\
\text{Fed funds rate expectations} &= 100(R - 1) + E_t\left[\frac{1}{40}\hat{R}_{t+j}\right], \quad j = 1, \ldots, 6 \\
\text{10-year Treasury yield} &= 100(R - 1) + E_t\left[\frac{1}{40}\sum_{j=0}^{39}\hat{R}_{t+j}\right] + e_t^{10y} \\
\text{10-year inflation expectations} &= 100(\pi - 1) + E_t\left[\frac{1}{40}\sum_{j=0}^{39}\hat{\pi}_{t+j}\right] \\
\text{TFP growth, demeaned} &= \hat{z}_t^* + \frac{\alpha}{1-\alpha}(\hat{u}_t - \hat{u}_{t-1}) + e_t^{tfp} \\
\text{Aaa - 20-year Treasury spread} &= 100\ln(\varepsilon^{liq}) + E_t\left[\frac{1}{80}\sum_{j=0}^{79}\hat{\varepsilon}_{t+j}^{liq}\right] + e_t^{Aaa}
\end{aligned}$$

$$\text{Baa - 20-year Treasury spread} = 100\ln\left(\varepsilon^{liq}\varepsilon^{safe}SP_*\right) + E_t\left[\frac{1}{80}\sum_{j=0}^{79}(\hat{\hat{R}}^k_{t+j+1} - \hat{R}_{t+j})\right] + e^{Baa}_t \quad \text{(DGGT, Augmented)}$$

$$= 100\ln\left(\varepsilon^{liq}\varepsilon^{safe}SP_*\frac{d^{NBFI}}{l^{NBFI}}\right) + E_t\left[\frac{1}{80}\sum_{j=0}^{79}(\hat{\hat{R}}^k_{t+j+1} - \hat{R}_{t+j})\right] + e^{Baa}_t \quad \text{(NBFI)}$$

$$\text{3-month CD rate} = 100(R\varepsilon^{liq}\varepsilon^{safe} - 1) + \hat{R}^{d,b}_t \quad \text{(Augmented)}$$

$$\text{3-month P1CP rate} = 100(R\varepsilon^{liq}\varepsilon^{safe} - 1) + \hat{R}^{d,NBFI}_t + e^{R^{NBFI}}_t \quad \text{(NBFI)}$$

$$\text{Bank-loans-share growth} = \hat{l}^{b,share}_t - \hat{l}^{b,share}_{t-1} \quad \text{(NBFI)}$$

$\bar{L}$ is the mean level of hours worked, which is estimated. δ_{gdpdef} and γ_{gdpdef} allow for a different "matching function" between the model concept of inflation and the GDP deflator measure with respect to core PCE inflation. SP_* is an estimated interest rate spread. $\frac{d^{NBFI}}{l^{NBFI}}$ is an additional steady-state spread component arising from the decreasing returns to scale in the technology of NBFIs.

5.4 Data

5.4.1 Sources

Data construction for the observables used in the benchmark estimation strictly follows DGGT. Data on nominal GDP [GDP], nominal GDI [GDI], the GDP deflator [GDPDEF], core PCE inflation [PCEPILFE], nominal personal consumption expenditures [PCE], and nominal fixed private investment [FPI] are produced at a quarterly frequency by the Bureau of Economic Analysis (BEA) and are included in the National Income and Product Accounts (NIPA). Average weekly hours of production and nonsupervisory employees for total private industries [AWHNONAG], civilian employment [CE16OV], and the civilian non-institutional population [CNP16OV] are produced by the Bureau of Labor Statistics (BLS) at a monthly frequency. The first of these series is obtained from the Establishment Survey, and the remaining from the Household Survey. Both surveys are released in the BLS Employment Situation Summary. We take quarterly averages of the monthly data. Compensation per hour for the non-farm business sector [COMPNFB] is obtained from the Labor Productivity and Costs release and is produced by the BLS at a quarterly frequency. The federal funds rate [DFF] is obtained from the Federal Reserve Board's H.15 release at a business day frequency. The 10-year Treasury yield (zero-coupon, continuously compounded) series [SVENY10] is made available by the Board of Governors of the Federal Reserve System at a business day frequency. Corporate-Treasury spreads are computed as the difference between the Moody's seasoned Baa (Aaa) corporate bond yield [BAA] ([AAA]) and the yield on U.S. Treasury securities at 20-year constant maturity [GS20], also at a business day frequency (all data obtained from the Federal Reserve Board's H.15 release). We take quarterly averages of the annualized daily data. Quarterly data on 10-year CPI inflation expectations are made available by the Federal Reserve Bank of Philadelphia: these combine the series from the Survey of Professional Forecasters [INFCPI10YR] since 1991:IV and data from the Blue Chip Economic Indicators from 1979:IV to 1991:I. The measure for TFP growth is from Fernald (2014),[34] whose updated series (unadjusted for utilization) is made available by the Federal Reserve Bank of San Francisco at a quarterly frequency [dtfp; alpha]. Lastly, data on interest rate expectations, from 1 to 6 quarters ahead, are taken directly from the DGGT dataset,[35] since they use internal data from the Federal Reserve Board on the implied federal funds rate derived from OIS quotes.

Turning to the Augmented estimation, our baseline measure for the deposit rate is the secondary market rate on 3-month CDs, which comes from the OECD Main Economic Indicators database [IR3TCD01USQ156N] and is available at a quarterly frequency. The alternative series for the 1- [CD1M] and 6-month secondary market CD rates [CD6M], both discontinued in July 2013, are obtained from the Federal Reserve Board's H.15 release (monthly averages of business-day data). The M2 own rate series [M2OWN], discontinued in July 2019, was made available by the Board of Governors of the Federal Reserve System at a monthly frequency. Our last measure is the savings deposit rate from Drechsler et al. (2017), who gather monthly bank data from U.S. Call reports and compute the average interest rate paid on different forms of deposits by U.S. commercial banks. We take quarterly averages of the monthly data.

Our proxy for the interest rate on non-bank deposits is constructed by combining two sources: the interest rate on 3-month prime commercial paper [WCP3M], available from 1971:II to 1996:IV (Federal Reserve Board's H.15 release), and the 90-day AA nonfinancial commercial paper interest rate [RIFSPPNAAD90NB], available from 1997:I (Board of Governors of the Federal Reserve System). The former is available at a weekly frequency, the latter at a business day frequency, and we take quarterly averages of both. Data on bank and non-bank loans are from Table B.103 of the Financial Accounts of the United States Z.1 release, *i.e.* we consider the liabilities of the Nonfinancial Corporate Business sector: bank credit is the sum of Other Loans and Advances [OLALBSNNCB] and Bank Loans Not Elsewhere Classified [BLNECLBSNNCB], while non-bank credit is the sum of Commercial Paper [CPLBSNNCB] and Corporate Bonds [CBLBSNNCB], all available at a quarterly frequency.

5.4.2 Transformations

Following DGGT, civilian population data are treated with a Hodrick-Prescott filter. The resulting series is used to transform GDP, GDI, consumption, investment, and hours worked in per-capita terms. GDP, GDI, consumption, investment, and wages are also set in real terms by dividing them by the GDP deflator. The fed funds rate, the 10-year Treasury yield, the corporate-Treasury spreads, 10-year inflation expectations, and both bank and non-bank deposit rates are divided by 4 to express them in quarterly terms. 10-year inflation is further adjusted for the average differential between CPI and GDP deflator inflation. Finally, the TFP growth series is demeaned, divided by 4 (to convert it into quarterly growth rates), and divided by Fernald (2014) estimate of the labor share to express it in labor-augmenting terms.

$$\text{Output growth} = 100\Delta \ln[(GDP/GDPDEF)/CNP16OV]$$

[34] Available at `https://www.frbsf.org/economic-research/indicators-data/total-factor-productivity-tfp/`.

[35] Available at `https://github.com/FRBNY-DSGE/rstarBrookings2017`.

$$
\begin{aligned}
&= 100\Delta\ln[(GDI/GDPDEF)/CNP16OV] \\
\text{Consumption growth} &= 100\Delta\ln[(PCEC/GDPDEF)/CNP16OV] \\
\text{Investment growth} &= 100\Delta\ln[(FPI/GDPDEF)/CNP16OV] \\
\text{Wage growth} &= 100\Delta\ln(COMPNFB/GDPDEF) \\
\text{Hours worked} &= 100\ln[(AWHNONAG)(CE16OV/100)/CN16OV] \\
\text{Core PCE inflation} &= 100\Delta\ln(PCEPILFE) \\
\text{GDP deflator inflation} &= 100\Delta\ln(GDPDEF) \\
\text{Fed funds rate} &= DFF/4 \\
\text{Fed funds rate expectations} &= OIS/4 \\
\text{10-year bond yield} &= SVENY10/4 \\
\text{10-year inflation expectations} &= (INFCPI10YR - 0.5)/4 \\
\text{TFP growth, demeaned} &= (dtfp, demeaned)/[4(1 - alpha)] \\
\text{Aaa - 20-year Treasury spread} &= (AAA - GS20)/4 \\
\text{Baa - 20-year Treasury spread} &= (BAA - GS20)/4 \\
\text{3-month CD rate} &= IR3TCD01USQ156N/4 \\
\text{3-month P1CP rate} &= RIFSPPNAAD90NB/4 \\
\text{Bank-loans-share growth} &= 100\Delta\ln\left[\frac{OLALBS + BLNECLBS}{OLALBS + BLNECLBS + CPLBS + CBLBS}\right]
\end{aligned}
$$

5.5 Parameters

5.5.1 Description and priors

Table A1: Parameters' description and priors

Parameter	Description	Type	Prior Mean	SD
	Steady State			
100γ	Technology growth rate	N	0.400	0.100
α	Capital share	N	0.300	0.050
$100(\beta^{-1}-1)$	Discount rate	G	0.250	0.100
σ_c	Inverse EIS	N	1.500	0.370
h	Consumption habits	B	0.700	0.100
ν_l	Inverse Frisch elasticity	N	2.000	0.750
δ	Capital depreciation rate	-	0.025	-
Φ_p	Production fixed costs	-	1.000	-
S''	Investment adj. costs	N	4.000	1.500
ψ	Utilization costs	B	0.500	0.150
$\bar{L}$	Mean level of hours	N	-45.000	5.000
λ_w	SS wage markup	-	1.500	-
π_*	SS inflation	-	0.500	-
g_*	SS govt. spending	-	0.180	-
	Nominal Rigidities			
ζ_p	Calvo price stickiness	B	0.500	0.100

Table A1: Parameters' description and priors

Parameter	Description	Type	Prior Mean	SD
ζ_w	Calvo wage stickiness	B	0.500	0.100
ι_p	Price indexation	B	0.500	0.150
ι_w	Wage indexation	B	0.500	0.150
ε_p	Price Kimball curvature	-	10.000	-
ε_w	Wage Kimball curvature	-	10.000	-
	Policy			
ψ_1	Weight on inflation	N	1.500	0.250
ψ_2	Weight on output gap	N	0.120	0.050
ψ_3	Weight on output gap growth	N	0.120	0.050
ρ_R	Interest rate smoothing	B	0.750	0.100
	Financial Frictions			
$F(\bar{\omega})$	Entrepreneur SS prob. of default	-	0.030	-
SP_*	SS spread	G	1.000	0.100
$\zeta_{sp,b}$	Spread elasticity to leverage	B	0.050	0.005
γ_*	Entrepreneur survival prob.	-	0.990	-
α_{NBFI}	NBFI returns to scale (*)	-	0.990	-
ϑ	Banker survival prob. (*)	-	0.972	-
ε^{safe}	SS safety premium	-	0.000 (0.065)	-
ε^{liq}	SS liquidity premium	-	0.000 (0.117)	-
	Exogenous Processes			
ρ_g	Govt. spending a.c.	B	0.500	0.200
ρ_μ	MEI a.c.	B	0.500	0.200
ρ_{z^p}	Permanent technology a.c.	-	0.990	-
ρ_z	Stationary technology a.c.	B	0.500	0.200
$\rho_{liq,P}$	Permanent liquidity a.c.	-	0.990	-
$\rho_{liq,T}$	Transitory liquidity a.c.	B	0.500	0.200
$\rho_{safe,P}$	Permanent safety a.c.	-	0.990	-
$\rho_{safe,T}$	Transitory safety a.c.	B	0.500	0.200
ρ_{σ_ω}	Entrepreneur risk a.c.	B	0.750	0.150
ρ_{π_*}	Inflation target a.c.	-	0.990	-
ρ_{λ_f}	Price markup a.c.	B	0.500	0.200
ρ_{λ_w}	Wage markup a.c.	B	0.500	0.200
η_{λ_f}	Price markup MA coeff.	B	0.500	0.200
η_{λ_w}	Wage markup MA coeff.	B	0.500	0.200
ρ_{r^m}	Monetary policy a.c.	B	0.500	0.200
ρ_{Nb}	Banker net worth a.c. (*)	B	0.500	0.200
η_{gz}	Govt. spending/technology corr.	B	0.500	0.200
σ_g	Govt. spending s.d.	IG	0.100	2.000
σ_μ	MEI s.d.	IG	0.100	2.000
σ_{z^p}	Permanent technology s.d.	IG	0.100	2.000
σ_z	Stationary technology s.d.	IG	0.100	2.000
$\sigma_{liq,P}$	Permanent liquidity s.d.	IG	0.030	6.000
$\sigma_{liq,T}$	Transitory liquidity s.d.	IG	0.100	2.000
$\sigma_{safe,P}$	Permanent safety s.d.	IG	0.030	6.000
$\sigma_{safe,T}$	Transitory safety s.d.	IG	0.100	2.000

Table A1: Parameters' description and priors

Parameter	Description	Type	Prior Mean	SD
σ_{σ_ω}	Entrepreneur risk s.d.	IG	0.050	4.000
σ_{π_*}	Inflation target s.d.	IG	0.030	6.000
σ_{λ_f}	Price markup s.d.	IG	0.100	2.000
σ_{λ_w}	Wage markup s.d.	IG	0.100	2.000
σ_{r^m}	Monetary policy s.d.	IG	0.100	2.000
σ_{Nb}	Banker net worth s.d. (*)	IG	0.100	2.000
$\sigma_{1,r}$	1-quarter-ahead mon. policy s.d.	IG	0.200	4.000
$\sigma_{2,r}$	2-quarter-ahead mon. policy s.d.	IG	0.200	4.000
$\sigma_{3,r}$	3-quarter-ahead mon. policy s.d.	IG	0.200	4.000
$\sigma_{4,r}$	4-quarter-ahead mon. policy s.d.	IG	0.200	4.000
$\sigma_{5,r}$	5-quarter-ahead mon. policy s.d.	IG	0.200	4.000
$\sigma_{6,r}$	6-quarter-ahead mon. policy s.d.	IG	0.200	4.000
	Measurement			
δ_{gdpdef}	GDP deflator param. 1	N	0.000	2.000
γ_{gdpdef}	GDP deflator param. 2	N	1.000	2.000
ρ_{gdp}	GDP growth a.c.	N	0.000	0.200
ρ_{gdi}	GDI growth a.c.	N	0.000	0.200
ρ_{gdp}	GDP/GDI corr.	N	0.000	0.400
ρ_{gdpdef}	GDP deflator a.c.	B	0.500	0.200
ρ_{pce}	PCE inflation a.c.	B	0.500	0.200
ρ_{AAA}	Aaa-Treasury spread a.c.	B	0.500	0.100
ρ_{BBB}	Baa-Treasury spread a.c.	B	0.500	0.100
ρ_{10y}	10-year yield a.c.	B	0.500	0.200
ρ_{tfp}	TFP growth a.c.	B	0.500	0.200
$\rho_{R^{NBFI}}$	NBFI deposit rate a.c. (*)	B	0.500	0.200
σ_{gdp}	GDP growth s.d.	IG	0.100	2.000
σ_{gdi}	GDI growth s.d.	IG	0.100	2.000
σ_{gdpdef}	GDP deflator s.d.	IG	0.100	2.000
σ_{pce}	PCE inflation s.d.	IG	0.100	2.000
σ_{AAA}	Aaa-Treasury s.d.	IG	0.100	2.000
σ_{BBB}	Baa-Treasury s.d.	IG	0.100	2.000
σ_{10y}	10-year yield s.d.	IG	0.750	2.000
σ_{tfp}	TFP growth s.d.	IG	0.100	2.000
$\sigma_{R^{NBFI}}$	NBFI deposit rate s.d. (*)	IG	0.100	2.000

Note: For Inverse Gamma (IG) prior mean and standard deviation, τ and ν reported. When the type and the standard deviation of a prior are not specified, the parameter of interest is fixed. Terms in round brackets refer to the prior specifications used in the estimation of DGGT, when different from the baseline Augmented and NBFI priors. Parameters denoted with (*) are specific to the NBFI-model estimation.

5.5.2 Posterior estimates

Table A2: Parameters' Estimates

Parameter	DGGT Posterior Mean	Augmented Posterior Mean	Augmented 90.0% L.	Augmented 90.0% U.	NBFI Posterior Mean	NBFI 90.0% L.	NBFI 90.0% U.
			Steady State				
100γ	0.434	0.418	0.342	0.495	0.429	0.344	0.510
α	0.187	0.225	0.206	0.244	0.118	0.104	0.132
$100(\beta^{-1}-1)$	0.287	0.135	0.065	0.206	0.114	0.043	0.183
σ_c	0.903	1.303	1.172	1.426	1.420	1.148	1.696
h	0.495	0.208	0.159	0.257	0.310	0.216	0.397
ν_l	2.482	2.618	1.728	3.486	2.815	2.072	3.527
δ	0.025	0.025	-	-	0.025	-	-
Φ_p	1.000	1.000	-	-	1.000	-	-
S''	1.466	4.818	3.315	6.292	4.056	3.281	4.751
ψ	0.615	0.683	0.574	0.801	0.714	0.561	0.867
δ_{gdpdef}	0.001	0.008	-0.028	0.044	0.013	-0.030	0.055
$\bar{L}$	-47.413	-47.538	-49.924	-45.276	-46.009	-48.320	-43.700
λ_w	1.500	1.500	-	-	1.500	-	-
π_*	0.500	0.500	-	-	0.500	-	-
g_*	0.180	0.180	-	-	0.180	-	-
			Nominal Rigidities				
ζ_p	0.957	0.952	0.943	0.961	0.951	0.940	0.961
ζ_w	0.967	0.962	0.956	0.968	0.971	0.967	0.976
ι_p	0.210	0.253	0.110	0.385	0.261	0.124	0.405
ι_w	0.821	0.809	0.713	0.913	0.897	0.835	0.958
ε_p	10.000	10.000	-	-	10.000	-	-
ε_w	10.000	10.000	-	-	10.000	-	-
			Policy				
ψ_1	1.797	1.649	1.367	1.929	1.221	1.062	1.375
ψ_2	0.277	0.191	0.147	0.236	0.088	0.058	0.121
ψ_3	0.335	0.371	0.320	0.426	0.284	0.231	0.338
ρ_R	0.856	0.819	0.777	0.861	0.670	0.603	0.736
			Financial Frictions				
$F(\bar{\omega})$	0.030	0.030	-	-	0.030	-	-
SP_*	1.047	0.970	0.807	1.137	1.222	1.064	1.373
$\zeta_{sp,b}$	0.045	0.049	0.042	0.055	0.042	0.037	0.048
γ_*	0.990	0.990	-	-	0.990	-	-
α_{NBFI}	-	-	-	-	0.990	-	-
ϑ	-	-	-	-	0.972	-	-
ε^{safe}	0.065	0.000	-	-	0.000	-	-
ε^{liq}	0.117	0.000	-	-	0.000	-	-
			Exogenous Processes				
ρ_g	0.991	0.992	0.986	0.998	0.989	0.985	0.994
ρ_μ	0.237	0.340	0.254	0.428	0.388	0.223	0.547
ρ_{z^p}	0.990	0.990	-	-	0.990	-	-
ρ_z	0.935	0.963	0.944	0.975	0.967	0.956	0.980
$\rho_{liq,P}$	0.990	0.990	-	-	0.990	-	-
$\rho_{liq,T}$	0.870	0.489	0.252	0.730	0.459	0.192	0.721

Table A2: Parameters' Estimates

Parameter	DGGT Posterior Mean	Augmented Posterior Mean	Augmented 90.0% L.	Augmented 90.0% U.	NBFI Posterior Mean	NBFI 90.0% L.	NBFI 90.0% U.
$\rho_{safe,P}$	0.990	0.990	-	-	0.990	-	-
$\rho_{safe,T}$	0.626	0.593	0.381	0.809	0.489	0.207	0.760
ρ_{σ_ω}	0.987	0.957	0.938	0.976	0.963	0.934	0.989
ρ_{π_*}	0.990	0.990	-	-	0.990	-	-
ρ_{λ_f}	0.807	0.850	0.782	0.917	0.824	0.737	0.911
ρ_{λ_w}	0.324	0.342	0.099	0.560	0.884	0.878	0.892
η_{λ_f}	0.596	0.677	0.543	0.841	0.685	0.549	0.836
η_{λ_w}	0.402	0.412	0.207	0.604	0.891	0.885	0.898
η_{gz}	0.500	0.410	0.130	0.687	0.531	0.237	0.820
ρ_{r^m}	0.191	0.110	0.038	0.182	0.215	0.101	0.332
ρ_{Nb}	-	-	-	-	0.946	0.914	0.981
σ_g	2.240	2.350	2.142	2.553	2.268	2.070	2.456
σ_μ	0.422	0.665	0.584	0.748	0.602	0.521	0.684
σ_{z^p}	0.050	0.073	0.062	0.083	0.061	0.047	0.074
σ_z	0.522	0.556	0.506	0.608	0.556	0.507	0.604
$\sigma_{liq,P}$	0.019	0.021	0.018	0.023	0.012	0.011	0.012
$\sigma_{liq,T}$	0.067	0.014	0.013	0.015	0.036	0.031	0.040
$\sigma_{safe,P}$	0.013	0.014	0.013	0.015	0.029	0.026	0.032
$\sigma_{safe,T}$	0.155	0.031	0.028	0.034	0.035	0.030	0.041
σ_{σ_ω}	0.067	0.138	0.097	0.177	0.149	0.080	0.227
σ_{π_*}	0.056	0.063	0.049	0.076	0.030	0.020	0.039
σ_{λ_f}	0.067	0.060	0.043	0.076	0.068	0.052	0.084
σ_{λ_w}	0.395	0.399	0.359	0.445	0.378	0.344	0.414
σ_{r^m}	0.225	0.238	0.218	0.256	0.224	0.205	0.244
σ_{Nb}	-	-	-	-	1.316	1.041	1.575
$\sigma_{1,r}$	0.092	0.100	0.075	0.118	0.098	0.079	0.124
$\sigma_{2,r}$	0.090	0.087	0.066	0.105	0.081	0.065	0.095
$\sigma_{3,r}$	0.088	0.084	0.070	0.097	0.083	0.065	0.100
$\sigma_{4,r}$	0.092	0.095	0.072	0.111	0.085	0.068	0.099
$\sigma_{5,r}$	0.090	0.095	0.073	0.128	0.088	0.072	0.105
$\sigma_{6,r}$	0.086	0.088	0.072	0.103	0.094	0.078	0.111
			Measurement				
δ_{gdpdef}	0.001	0.008	-0.028	0.044	0.013	-0.030	0.055
γ_{gdpdef}	1.047	1.031	0.962	1.101	1.027	0.954	1.099
ρ_{gdp}	0.017	0.023	-0.213	0.242	-0.009	-0.229	0.211
ρ_{gdi}	0.947	0.941	0.907	0.975	0.940	0.902	0.973
ρ_{gdp}	-0.154	-0.183	-0.809	0.402	-0.178	-0.806	0.414
ρ_{gdpdef}	0.412	0.401	0.266	0.538	0.416	0.284	0.548
ρ_{pce}	0.222	0.254	0.072	0.421	0.233	0.060	0.389
ρ_{AAA}	0.639	0.722	0.613	0.837	0.750	0.667	0.832
ρ_{BBB}	0.913	0.954	0.939	0.969	0.892	0.856	0.926
ρ_{10y}	0.951	0.946	0.919	0.979	0.944	0.914	0.976
ρ_{tfp}	0.271	0.272	0.157	0.380	0.287	0.177	0.394
$\rho_{R^{NBFI}}$	-	-	-	-	0.465	0.183	0.736
σ_{gdp}	0.243	0.241	0.200	0.285	0.244	0.200	0.289

Table A2: Parameters' Estimates

Parameter	DGGT Posterior Mean	Augmented Posterior Mean	90.0% L.	90.0% U.	NBFI Posterior Mean	90.0% L.	90.0% U.
σ_{gdi}	0.311	0.308	0.275	0.347	0.312	0.277	0.346
σ_{gdpdef}	0.171	0.173	0.159	0.186	0.175	0.160	0.188
σ_{pce}	0.116	0.119	0.103	0.134	0.118	0.101	0.135
σ_{AAA}	0.022	0.027	0.024	0.031	0.035	0.033	0.038
σ_{BBB}	0.050	0.059	0.054	0.064	0.063	0.060	0.067
σ_{10y}	0.123	0.121	0.112	0.130	0.127	0.115	0.136
σ_{tfp}	0.667	0.619	0.554	0.685	0.712	0.650	0.774
$\sigma_{R^{NBFI}}$	-	-	-	-	0.037	0.032	0.042

6 Robustness checks on the Augmented estimation

This section presents the main results from a set of robustness exercises on the Augmented estimation. We first re-estimate the model imposing the steady-state calibration of DGGT concerning safety and liquidity premiums. Then, we test the validity of our baseline results using two alternative proxies for the bank deposit rate.

6.1 Estimation with alternative calibration

In the baseline Augmented estimation, we demeaned the corporate spreads to make the steady-state calibration consistent with the observed CD rate. We now reintroduce the "original" Baa- and Aaa-Treasury spreads as observables (not demeaned), and fix the liquidity and safety premiums as in DGGT. As a consequence, the steady-state deposit rate is assumed to be 73 basis points higher than the fed funds rate.

Parameter estimates are virtually unchanged with respect to our baseline specification.[36] Results in terms of historical decomposition also replicate our baseline findings, as reported in Figure B1, except for slight differences in the real policy and the natural rates. There is a small and nearly constant positive contribution of liquidity shocks to the real policy rate, which is reflected in the estimate of the natural interest rate. This is directly linked to the different calibration, and to the aforementioned steady-state premium of the deposit rate over the policy rate. Because the CD rate in the data is closer to the fed funds rate (on average) than implied by the calibration, the model identifies a sequence of negative liquidity shocks that raises the policy rate and is able to cancel the model-imposed wedge.

6.2 Estimation with alternative data

The alternative deposit rate measures we use as observables are the M2 own rate and the savings deposit rate. The M2 own rate is available up to 2019:II, whereas the savings deposit rate series spans from 1986:I to 2013:IV. Figure B2 shows the two series as opposed to the fed funds rate.

Both series display a substantial and negative differential with respect to the fed funds rate. In fact, the savings deposit is a more liquid saving instrument than the certificate of

[36] A full description of the posterior estimates of this and of the following robustness exercises is available upon request.

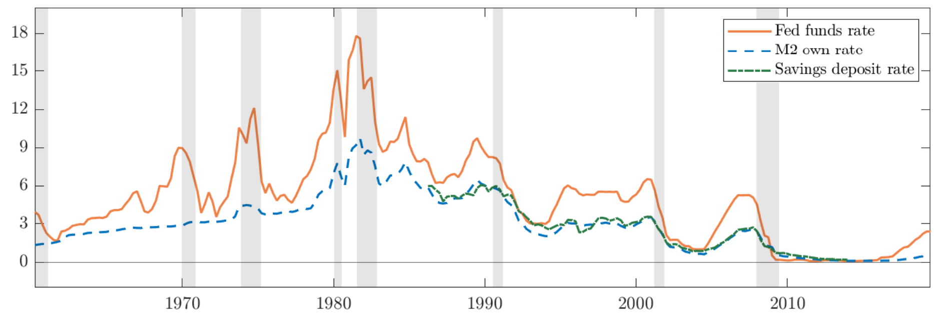
Figure B1: Historical shock decomposition (Augmented, alternative calibration)

Note: Historical shock decomposition at the posterior mode. "Liquidity": sum of transitory liquidity, transitory safety, permanent liquidity, and permanent safety shocks; "Productivity": sum of stationary and permanent technology shocks; "Monetary policy": sum of contemporaneous and anticipated monetary policy shocks; "Other": sum of all other shocks and measurement errors, and initial values. 2000:I-2019:IV.

deposit. The M2 aggregate similarly comprises several assets that are more liquid than CDs (including savings deposits). We see that the two series, when jointly available, are fairly close in terms of level and co-movement. Indeed, estimates turn out to be similar using the two proxies (this appendix reports the results obtained with the M2 own rate only).

When we estimate the model matching the M2 own rate, we observe meaningful variations in the posterior of some crucial parameters. In particular, the estimated autocorrelation of *transitory* liquidity (and safety) shocks is around 0.9, implying that the model requires

Figure B2: Fed funds rate vs alternative deposit rate measures

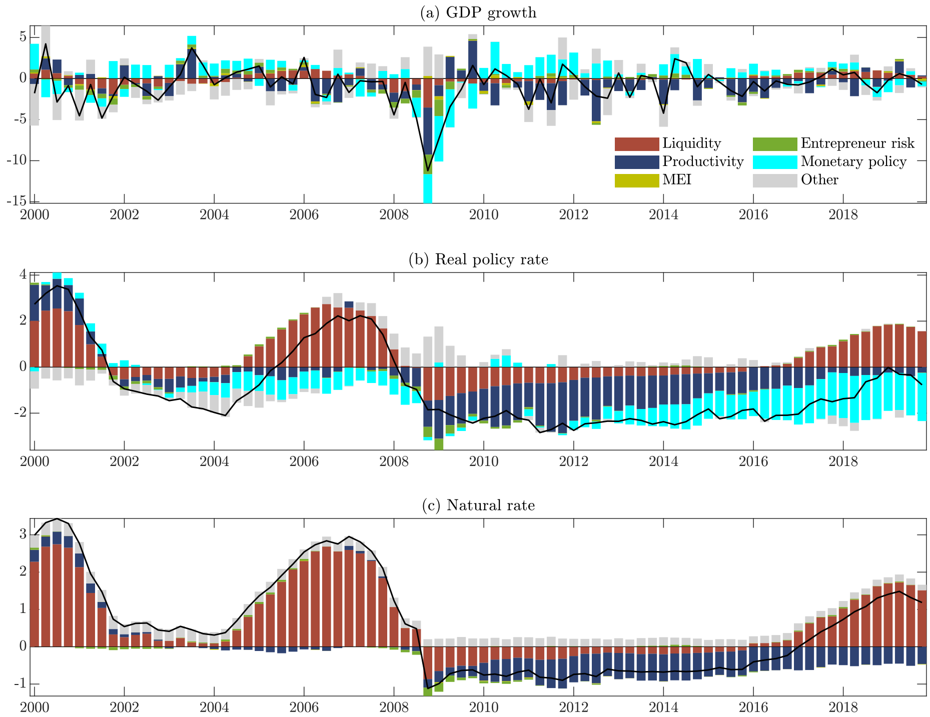


Note: The fed funds rate and the M2 own rate are plotted from 1960:I to 2019:II. The savings deposit rate is from Drechsler et al. (2017), and is displayed over the period 1986:I-2013:IV.

all flight-to-quality shocks to be highly persistent in order to match the deviations between the fed funds rate and the deposit rate. Moreover, the posterior mean of the inverse EIS σ_c is extremely small (0.41) and, combined with the estimate of β (0.999), entails a low steady-state real interest rate of 1.04%.

Figure B3 shows the historical decomposition of GDP growth, the real policy rate, and the natural rate. The role of liquidity shocks in explaining GDP growth (top panel) is dominated by other disturbances, namely technology and monetary policy shocks, confirming our baseline results. Turning to the interest rates, there is a strong contribution by liquidity shocks (panels (b) and (c)). However, the largest part of their impact consists in *raising* the policy rate, at least up to 2008. Even thereafter, their contribution to dragging the real fed funds rate down is small compared to technology shocks; after 2017, they explain the departure from the ZLB. This result stems from the low steady-state real interest rate: the model estimates this value to be closer to the average deposit rate than to the fed funds rate, and then attributes the rise of the policy rate with respect to its steady state to a series of negative liquidity shocks. Since these shocks are persistent, the natural interest rate is estimated to be exceptionally less volatile and closer to the actual real rate than in DGGT (see Figure E4).

Figure B3: Historical shock decomposition (Augmented, M2 own rate observed)

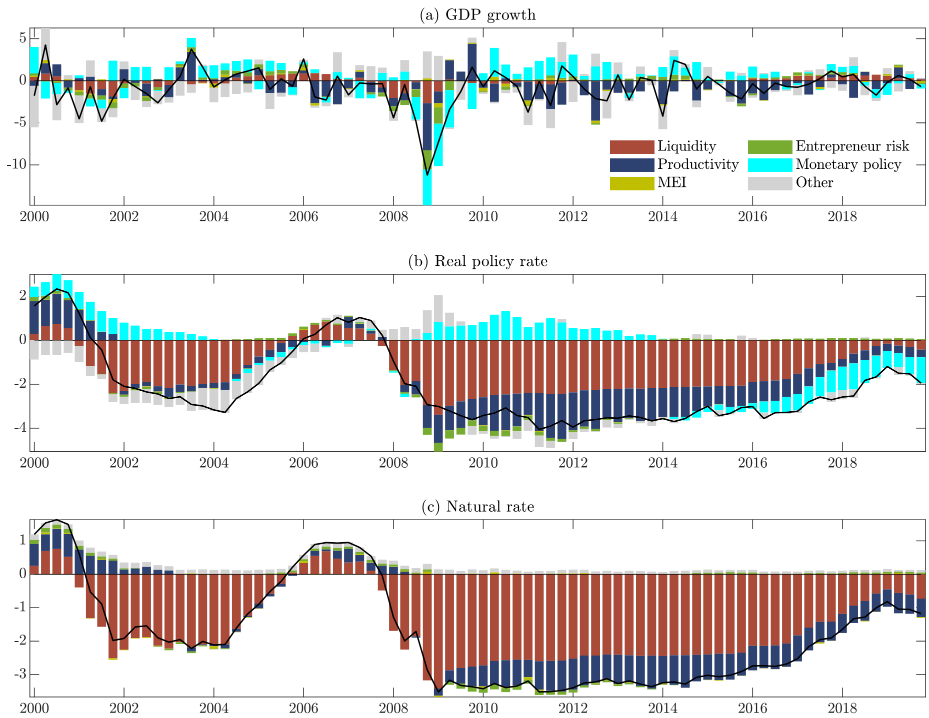


Note: Historical shock decomposition at the posterior mode. “Liquidity”: sum of transitory liquidity, transitory safety, permanent liquidity, and permanent safety shocks; “Productivity”: sum of stationary and permanent technology shocks; “Monetary policy”: sum of contemporaneous and anticipated monetary policy shocks; “Other”: sum of all other shocks and measurement errors, and initial values. 2000:I-2019:IV.

We conduct a final robustness check by shifting the M2 own rate upwards to have the same sample mean as the 3-month CD rate over the period 1964:III-2016:III, and by estimating the model with this new measure. We are so able to remove the observed negative differential between the M2 own rate and the fed funds rate, which is at odds with the assumptions of the benchmark model. Though evidently artificial, this adjustment may be rationalized with a premium for the transaction services provided by the assets included in M2. Such a premium is not modeled and thus is cleared away from the data.

This new estimation yields parameter estimates that are close to the version with the unadjusted M2 own rate, *i.e.* a low σ_c (0.57) and high autocorrelation coefficient for all liquidity shocks (larger than 0.86).[37] The shock decomposition of GDP growth is also virtually unaffected by the adjustment of the M2 own rate (see panel (a) of Figure B4). On the other hand, the picture for the real policy rate is similar to the benchmark estimation without the observed deposit rate, with liquidity shocks pushing down interest rates following the financial crisis. Still, the estimated path of the natural rate is strikingly different with respect to the one found by DGGT, as Figure E4 shows.

Figure B4: Historical shock decomposition (Augmented, adjusted M2 own rate observed)



Note: Historical shock decomposition at the posterior mode. "Liquidity": sum of transitory liquidity, transitory safety, permanent liquidity, and permanent safety shocks; "Productivity": sum of stationary and permanent technology shocks; "Monetary policy": sum of contemporaneous and anticipated monetary policy shocks; "Other": sum of all other shocks and measurement errors, and initial values. 2000:I-2019:IV

In conclusion, even though the use of alternative deposit rate proxies allows for a larger influence of liquidity shocks with respect to our baseline, these are overshadowed by other shocks (mainly to productivity) and are effectively irrelevant for GDP growth after 2010. Additionally, the inclusion of a deposit rate measure that is farther from the fed funds rate, forces the model to explain the deposit spread with highly persistent liquidity shocks. This

[37]The discount rate β is instead estimated to be closer to the baseline, as is the steady state real interest rate. This follows from the upward shift of the deposit rate proxy.

has profound implications for the dynamics of the natural interest rate that gets remarkably closer to the real policy rate.

7 α_{NBFI} calibration

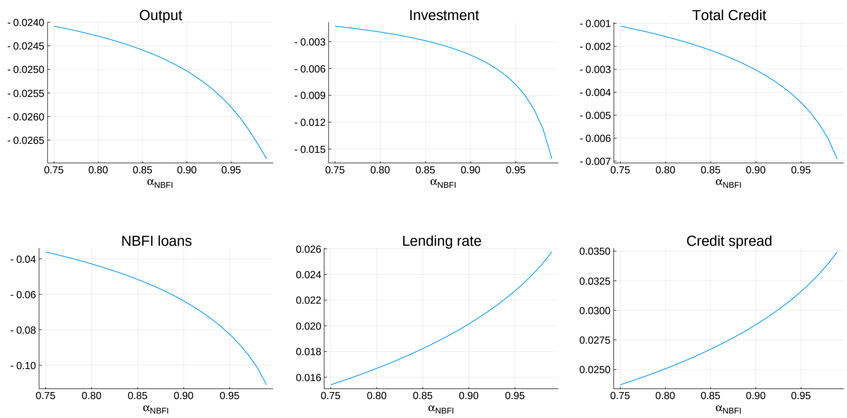
The parameter α_{NBFI} determines the degree of returns to scale in the NBFI-transformation of deposits into loans. As mentioned in Section 2.3, we do not impose constant returns to scale because this would lead to an indeterminate solution of our model. In fact, if we assumed $\alpha_{NBFI} = 1$, bank and non-bank credit would not be separately identified. The goal of our calibration strategy is therefore to choose a value for α_{NBFI} so as to maintain the transmission mechanism of liquidity shocks close to DGGT. As we show below, a relatively high value of α_{NBFI} safeguards liquidity shocks from having counterfactual implications for the co-movement between output, on the one hand, and investment and credit, on the other.

In order to understand the impact of α_{NBFI}, combine the log-linearized equilibrium conditions (1.A20) and (1.A21) to get an expression for the spread between lending and policy rates:

$$\hat{R}_t^L - \hat{R}_t = \hat{\varepsilon}_t^l + (1-\alpha_{NBFI})\hat{d}_t^{NBFI}. \tag{1.C1}$$

When an adverse liquidity shock hits (*i.e.* a positive realization of $\hat{\varepsilon}_t^l$), the spread widens, but there is a simultaneous force that pulls in the opposite direction. Consistently with a flight to quality, the amount of deposits held at NBFIs, $\hat{d}_t^{NBFI}$, decreases and reduces the spread. As is clear from (1.C1), the larger α_{NBFI}, the smaller the dampening effect of NBFI deposits. Further, looking at (1.A23), as α_{NBFI} increases, the reduction in NBFI loans is larger following a liquidity shock.

Figure C1: Impact responses to an adverse transitory liquidity shock (NBFI)



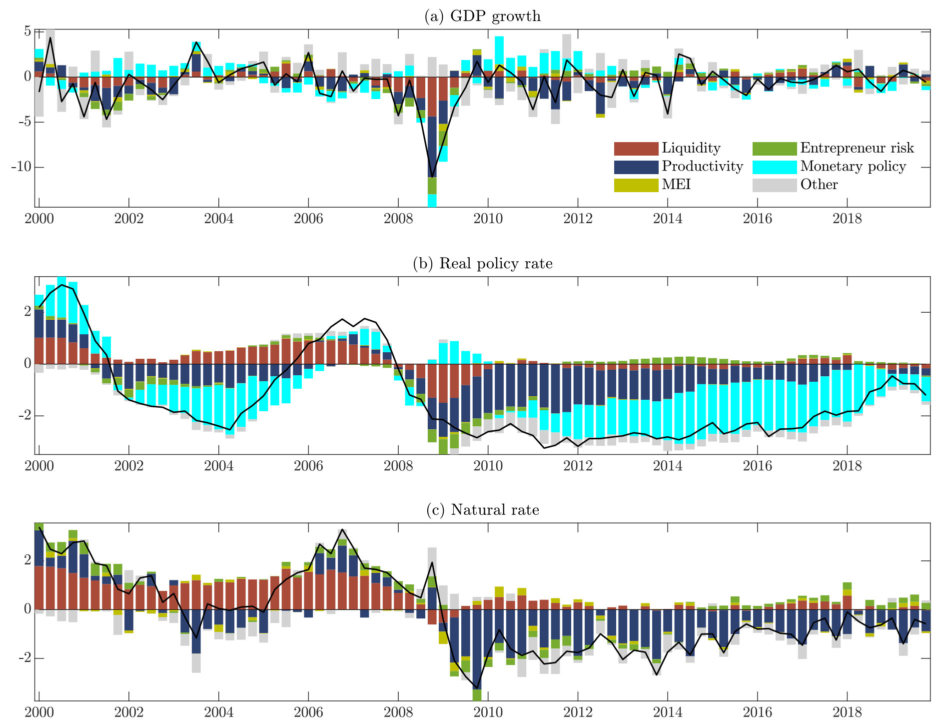
Note: Estimated impact responses at the posterior mode.

Figure C1 shows the estimated response of selected variables on impact, after an adverse liquidity shock, for a range of α_{NBFI} values that goes from 0.75 to 0.99. In line with the previous discussion, as we move to the left of the α_{NBFI}-grid, lending rates and the credit spread increase by less, while NBFI loans decrease by less. This prompts a smaller reduction in credit, and eventually in investment. For smaller values of α_{NBFI} and/or a different autocorrelation coefficient of the shock, the response of credit and investment may turn countercyclical (notice how the impact response of output is relatively more stable). In this sense, the choice of $\alpha_{NBFI} = 0.99$ is "conservative" and allows credit to co-move with output, consistently with the behavior induced by liquidity shocks in DGGT (see Figure 5).

8 Alternative NBFI estimation

We conduct an alternative estimation of the NBFI model, where the bank-loans-share growth rate is the only additional observable with respect to DGGT. The model is thus not constrained to match the P1CP rate as a measure of the non-bank deposit rate. As shown in Figure 7, this estimation leads to a mismatch between the model-implied NBFI deposit rate and the observed return on P1CP. Though apparently small, this gap is sufficient to generate a quite relevant role for liquidity shocks as a driver of GDP growth. However, as evident in panel (a) of Figure D1, the predominance of flight-to-quality shocks is limited to the Great Recession period.

Figure D1: Historical shock decomposition (NBFI, P1CP rate not observed)



Note: Historical shock decomposition at the posterior mode. "Liquidity": sum of transitory liquidity, transitory safety, permanent liquidity, and permanent safety shocks; "Productivity": sum of stationary and permanent technology shocks; "Monetary policy": sum of contemporaneous and anticipated monetary policy shocks; "Other": sum of all other shocks and measurement errors, and initial values.

As shown in panel (b), there is a widespread contribution of monetary policy shocks to the real fed funds rate dynamics. This channel is stronger than in our baseline NBFI estimation, especially between 2002 and 2006, and after 2012. The natural rate is exceptionally less volatile than in DGGT, and liquidity shocks play virtually no role in explaining its decline (panel (c)). Surprisingly enough, the estimated pattern of r^* since the mid-80s is roughly in line with those predicted by the alternative Augmented estimates (*i.e.* with the

M2 own rate as bank deposit rate; see Figure E4). If anything, these alternative estimates suggest that monetary policy was even more expansionary than implied by our baseline, at least after the 2007-08 financial crisis.

9 Additional tables and figures

9.1 Tables

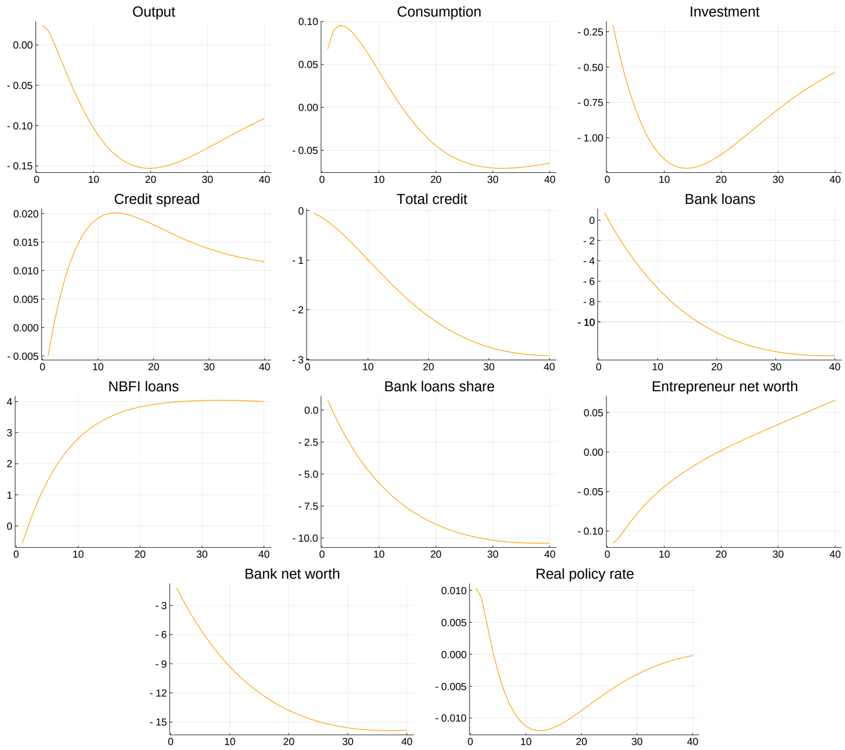
Table E1: Variance decomposition (full sample)

	Liquidity	Tech.	MEI	Risk	Govt.	Monetary	Markup	Bank n.w.	m.e.
GDP growth									
DGGT	24%	25%	3%	3%	11%	17%	3%	-	14%
Augmented	3%	36%	14%	5%	8%	17%	2%	-	15%
NBFI	3%	39%	8%	3%	10%	18%	2%	2%	15%
Consumption growth									
DGGT	30%	24%	3%	6%	14%	19%	4%	-	-
Augmented	4%	42%	3%	7%	18%	22%	3%	-	-
NBFI	5%	49%	3%	3%	11%	24%	2%	3%	-
Investment growth									
DGGT	24%	13%	9%	29%	1%	19%	5%	-	-
Augmented	1%	8%	56%	24%	1%	6%	2%	-	-
NBFI	2%	9%	54%	16%	2%	9%	4%	6%	-
Real policy rate									
DGGT	69%	12%	1%	2%	2%	11%	3%	-	-
Augmented	5%	29%	15%	18%	2%	27%	4%	-	-
NBFI	6%	35%	7%	9%	1%	35%	4%	3%	-
Aaa-Treasury spread									
DGGT	94%	-	-	-	-	-	-	-	6%
Augmented	74%	-	-	-	-	-	-	-	26%
NBFI	58%	-	-	-	-	-	-	-	42%
Baa-Treasury spread									
DGGT	32%	4%	2%	3%	4%	3%	3%	-	48%
Augmented	10%	17%	9%	9%	11%	9%	10%	-	26%
NBFI	5%	10%	2%	10%	0%	3%	1%	2%	67%

Note: Variance decomposition at the posterior mode. The percentage contribution is given by the variance of a variable accounted for by each of the listed (groups of) shocks divided by the summed variances of the same variable accounted for by all (groups of) shocks.

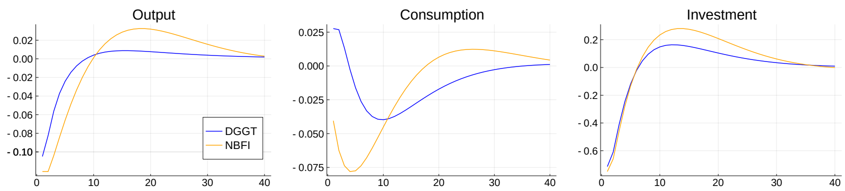
9.2 Figures

Figure E1: IRFs to an adverse bank net worth shock (NBFI)



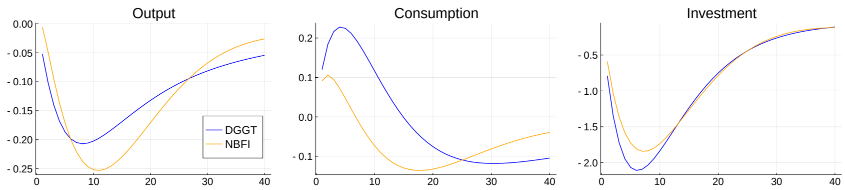
Note: Estimated impulse response functions at the posterior mode.

Figure E2: IRFs to an adverse MEI shock, selected macro aggregates (DGGT vs NBFI)



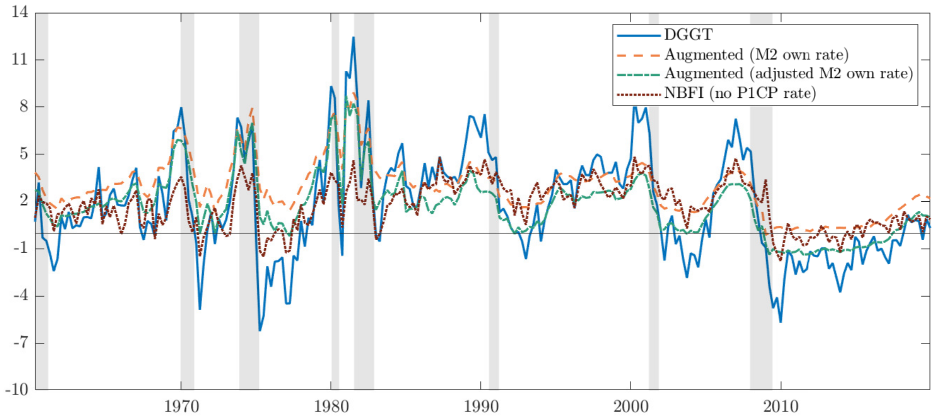
Note: Estimated impulse response functions at the posterior mode. The autocorrelation coefficient and the standard deviation of the shock are fixed at the DGGT-posterior-mode estimates.

Figure E3: IRFs to an adverse entrepreneur risk shock, selected macro aggregates (DGGT vs NBFI)



Note: Estimated impulse response functions at the posterior mode. The autocorrelation coefficient and the standard deviation of the shock are fixed at the DGGT-posterior-mode estimates.

Figure E4: Alternative r^* estimates



Note: Smoothed estimates of r^* at the posterior mode. 1960:I-2019:IV.