Stablecoins: The Good, the Bad, and the Ugly*

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Abstract

This paper develops a New Keynesian model with banks and stablecoins to study two consequences of private digital money. First, welfare is lower to the extent that stablecoin issuers capture seigniorage profits that would otherwise accrue to the public at large. These losses are smallest (zero) for CBDC-backed stablecoins ("good"), intermediate for deposit-backed stablecoins ("bad"), and largest for government-debt-backed stablecoins ("ugly"). Second, stablecoin issuance introduces an uncontrolled money-like aggregate that is not coordinated with monetary policy, and this has the potential to generate real and price instability. However, we find that in the presence of financial shocks and monetary policy shocks stablecoins in fact reduce instability, especially when they are CBDC-backed or government-debt-backed. In the presence of real shocks they do increase instability. The trade-off is therefore an empirical question that turns on the relative importance of financial and real shocks. However, when combined with the steady state effects, CBDC-backed stablecoins emerge as the clear frontrunner in terms of public welfare.

Keywords: Stablecoins; CBDCs; monetary policy transmission; seigniorage; bank intermediation; digital money; financial stability.
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1. Introduction

For several years central banks have been actively studying the possibility of issuing digital money to the public, a concept that has become known as central bank digital currencies, or CBDCs. The costs and benefits of this new form of monetary policy have been studied in a large literature. More recently a private alternative to CBDCs has emerged in the form of stablecoins. The stablecoin market has reached approximately $ 300 billion in market capitalization and is projected to grow to between $ 900 billion and $ 4 trillion by 2030. A recent ECB working paper (Altavilla et al., 2026) documents three key empirical findings using confidential euro area bank data: (i) stablecoin adoption triggers deposit substitution from retail to wholesale funding; (ii) this alters the pass-through of policy rates to lending conditions; and (iii) foreign-currency stablecoins can import external monetary conditions.

In this paper we will study the effects of stablecoins using a quantitative business cycle model. We will focus on two questions.

Seigniorage Redistribution: Our analysis starts from the present legal and regulatory reality that stablecoins cannot pay a nonzero interest rate. With CBDC-backed stablecoins the removal of government bonds from the private market reduces the free float of government debt that has to be absorbed by private markets. This in turn reduces the interest cost of government financing, first because CBDCs themselves carry the same zero interest rate as the stablecoins they back, and second because a lower free float reduces the interest rate on the remaining government debt. But when stablecoins are backed by government debt or bank deposits, the free float does not change, and furthermore the positive interest earned on reserve assets accrues to private issuers (Tether, Circle) rather than to the treasury, which could otherwise share these funds with the public. On the assumption that these funds are consumed by risk-neutral stablecoin issuers that represent an infinitesimal fraction of the population, this must reduce public welfare.

Real and Price Stability: The introduction of stablecoins creates new channels through which monetary liquidity adjusts to shocks. These channels can improve adjustment when they provide households and intermediaries with additional balance-sheet flexibility, but they can also increase real and price instability when stablecoin issuance generates portfolio shifts that are not coordinated with monetary policy. We therefore study the model both shock by shock and in unconditional simulations. The stablecoin-demand shock illustrates the importance of backing: deposit-backed stablecoins absorb most of the portfolio shift through the banking system, while CBDC-backed and government-debt-backed stablecoins transmit the shock more strongly to output, consumption, welfare, and inflation. Claims about whether stablecoins reduce instability relative to a no-stablecoin economy require a true no-stablecoin benchmark and shock-by-shock comparisons.

2. Literature

This paper is related first to the literature on central bank digital currencies and bank intermediation. A central theme in this literature is that digital public money can substitute for bank deposits and thereby affect lending, deposit competition, and monetary transmission. Andolfatto (2021) studies how CBDC affects private banks and shows that the effects depend on the structure of competition and on the central bank's policy design. Fernández-Villaverde et al. (2021) analyze central-bank-provided digital accounts and emphasize the interaction between CBDC, financial intermediation, and the payments role of deposits. Keister and Sanches (2023) study whether central banks should issue digital currency when private banks create deposits, while Agur et al. (2022) and Williamson (2022) characterize optimal CBDC design and welfare trade-offs. Barrdear and Kumhof (2022) provide a quantitative macroeconomic analysis of CBDC issuance, and Brunnermeier and Niepelt (2019) clarify conditions under which public and private money can be equivalent. Our paper differs from this strand by focusing on privately issued stablecoins rather than CBDC itself, and by asking how the backing asset of private digital money changes seigniorage, financial intermediation, and macroeconomic stability.

A second related strand studies CBDC in open economies and the international transmission of digital money. Minesso et al. (2022) show that CBDC issuance in one country can affect monetary autonomy and welfare abroad. Kumhof et al. (2023) study CBDC policies in open economies with banking frictions, and the policy reports by Auer et al. (2021), Kosse and Mattei (2022), and Committee on Payments and Market Infrastructures et al. (2021) document the growing policy interest in CBDCs and cross-border digital payments. These papers are relevant because dollar stablecoins already operate as cross-border private money. Our analysis abstracts from the open-economy dimension, but it shares the same concern that digital money changes the liabilities through which monetary policy is transmitted.

The paper is also closely related to the emerging literature on stablecoins. Gorton et al. (2022) interpret stablecoins through the lens of private money creation and emphasize the importance of backing, regulation, and convertibility. Lyons and Viswanath-Natraj (2023) study the mechanisms that keep stablecoins close to par, while Bertsch (2023) and d'Avernas et al. (2026) analyze adoption, fragility, and stability risks. Baughman and Flemming (2023) study global demand for basket-backed stablecoins. These papers focus primarily on stablecoin stability, adoption, and run risk. Our contribution is complementary: we take stablecoin par convertibility as maintained and study the macroeconomic consequences of different backing assets in a New Keynesian model with banks.

Most directly, the paper contributes to the literature on stablecoins and monetary policy transmission. Aldasoro et al. (2025) study stablecoins, money market funds, and monetary

policy, highlighting that stablecoins are connected to the broader system of safe, money-like assets. Altavilla et al. (2026) provide direct empirical evidence that stablecoin adoption affects deposits, bank funding, and the pass-through of monetary policy. We build on this evidence by introducing stablecoins into a quantitative monetary model and separating three backing structures: CBDC-backed stablecoins, deposit-backed stablecoins, and government-debt-backed stablecoins. This distinction is central for our results. CBDC-backed stablecoins do not transfer backing-asset income to private issuers, while deposit-backed and government-debt-backed stablecoins do. At the same time, the backing asset determines how stablecoin demand shocks are absorbed by banks, households, and the government balance sheet. The model therefore links two issues that are usually studied separately: the steady-state public-finance cost of private money creation and the business-cycle consequences of an additional money-like aggregate.

3. Model

The economy is populated by households, firms, banks, a stablecoin issuer, the central bank, and the government. Time is discrete, $t = 0, 1, 2, ...$, and trend growth equals zero. We denote nominal quantities and prices by upper case letters while their real counterparts are denoted by lower case letters. Real variables are the corresponding nominal variables divided by the consumer price index P_t. We denote gross nominal and real interest rates on an asset or liability z held between periods $t-1$ and t as i^z_{t-1} and $r^z_t = i^z_{t-1}/\pi_t$, where $\pi_t = P_t/P_{t-1}$ is the gross inflation rate. For a cash-like asset that pays a zero nominal interest rate, we adopt the notation $r^n_t = 1/\pi_t$. The expression $\Phi(.)$ denotes the cumulative distribution function of the standard normal distribution.

3.1. Banking Sector

3.1.1. Wholesale Banks

Wholesale banks have unit mass and are indexed by j, where individual banks differ by the size of their net worth. In equilibrium all wholesale banks face the same prices and risks, and receive the same lump-sum distributions relative to their net worth, so that their optimality conditions feature unique and identical loans-to-net-worth and deposits-to-net-worth ratios. In their optimality conditions the index j can therefore be dropped.

Wholesale banks' nominal assets are wholesale loans to retail lending banks $L_t(j)$ (with real loans denoted by $\ell_t(j)$) and their liabilities are deposits $O_t(j)$ from retail deposit banks, while their net worth or equity is $E_t(j)$. We substitute the constraint that deposits from retail deposit banks $O_t(j)$ equal deposits from households $D_t(j)$ and (potentially) deposits

from stablecoin issuers $D_t^{sc}(j)$. In real aggregate terms the balance sheet of wholesale banks is therefore given by

$$\ell_t = d_t + d_t^{sc} + e_t \,. \tag{1}$$

At the beginning of period $t+1$ each wholesale bank draws a shock ω_{t+1}^{bk} such that the return on its loan book equals $r_{t+1}^{\ell}\omega_{t+1}^{bk}$, where ω_{t+1}^{bk} is a unit mean lognormal random variable distributed independently over time and across banks. The standard deviation of $ln(\omega_{t+1}^{bk})$ equals $(\sigma_{bk})^2$, and the pdf and cdf of ω_{t+1}^{bk} are denoted by $f^{bk}(\omega_{t+1}^{bk})$ and $F^{bk}(\omega_{t+1}^{bk})$. This risk represents banks' differing success at raising non-interest net income, where the sum of net income equals zero over all banks.

Banks are subject to minimum capital adequacy ratios (MCAR) such that a fraction of banks has to pay a penalty of $\chi L_t(j)$ at time t+1 if the sum of their net interest earnings, retail deposit bank profits, and retail lending bank net losses is less than a fraction γ of the gross return on their loan book, so that γ can be interpreted as the Basel MCAR. The penalty, weighted by the probability of its occurrence, is incorporated into banks' optimal capital choice. Banks' actually maintained capital adequacy ratio γ_t^a remains considerably above the minimum requirement γ, because by maintaining an optimally chosen buffer banks protect themselves against the risk of penalties while minimizing the cost of excess capital. The penalty cutoff condition for bank j is given by

$$i_t^{\ell} L_t(j)\omega_{t+1}^{bk} - i_t\left(D_t(j) + D_t^{sc}(j)\right) + P_{t+1}\Pi_{t+1}^{rdb}(j) - P_{t+1}\Lambda_{t+1}^{rlb}(j) < \gamma i_t^{\ell} L_t(j)\omega_{t+1}^{bk},$$

where $\Lambda_{t+1}^{rlb}(j)$ are bank j's shares of the net losses of retail lending banks, and where the shares are lump-sum and pro-rated in proportion to each bank's net worth. The cutoff idiosyncratic shock to loan returns below which the MCAR is breached ex-post is $\bar{\omega}_t^{bk}(j) = (i_{t-1}\left(D_{t-1}(j) + D_{t-1}^{sc}(j)\right) - P_t\Pi_t^{rdb}(j) + P_t\Lambda_t^{rlb}(j))/((1-\gamma)i_{t-1}^{\ell}L_{t-1}(j))$. In real aggregate terms this equals

$$\bar{\omega}_t^{bk} = \frac{r_t\left(d_{t-1} + d_{t-1}^{sc}\right) - \Pi_t^{rdb} + \Lambda_t^{rlb}}{(1-\gamma)r_t^{\ell}\ell_{t-1}} \,. \tag{2}$$

We adopt the notation $f_{t+1}^{bk} = f^{bk}\left(\bar{\omega}_{t+1}^{bk}\right)$ and $F_{t+1}^{bk} = F^{bk}\left(\bar{\omega}_{t+1}^{bk}\right)$.

Banks choose the volume of loans to maximize their pre-dividend net worth,

$$Max\, \mathbb{E}_t[i_t^{\ell} L_t(j)\omega_{t+1}^{bk} - i_t\left(D_t(j) + D_t^{sc}(j)\right) + P_{t+1}\Pi_{t+1}^{rdb}(j) - P_{t+1}\Lambda_{t+1}^{rlb}(j) - \chi L_t(j)F^{bk}(\bar{\omega}_{t+1}^{bk}(j))],$$

where the last term equals expected penalties. We arrive at post-dividend net worth by deducting dividends $\delta_e E_t(j)$, which are paid out to financial investors in a lump-sum fashion, a specification that can be obtained by applying the "extended family" approach of Gertler and Karadi (2011). The optimality condition for loans is

$$\mathbb{E}_t\left(r_{t+1}^{\ell} - r_{t+1} - \chi\left(F_{t+1}^{bk} + f_{t+1}^{bk}\frac{r_{t+1} - (1-\gamma)r_{t+1}^{\ell}\bar{\omega}_{t+1}^{bk}}{(1-\gamma)r_{t+1}^{\ell}}\right)\right) = 0. \tag{3}$$

This states that banks' wholesale lending rate is at a premium over the policy rate by a margin that depends on the size of the MCAR γ, the penalty coefficient χ for breaching the MCAR, and expressions $F^{bk}(\omega_{t+1}^{bk})$ and $f^{bk}(\omega_{t+1}^{bk})$ that reflect the expected riskiness of banks and therefore the likelihood of a breach. The bank would charge this rate to a hypothetical borrower (not present in the model) with zero default risk.

The evolution of aggregate wholesale bank net worth is given by

$$e_t = r_t^{\ell}\ell_{t-1} - r_t\left(d_{t-1} + d_{t-1}^{sc}\right) - \mathcal{M}_t^{bk} + \Pi_t^{rdb} - \Lambda_t^{rlb} - \delta_e e_t\,, \tag{4}$$

where MCAR violation costs are given by

$$\mathcal{M}_t^{bk} = \chi F_t^{bk}\ell_{t-1}\,. \tag{5}$$

Finally, as shown in the Online Appendix, we have the following auxiliary relationships:

$$\bar{\omega}_t^{bk} = exp(\bar{z}_t^{bk}\sigma_{bk} - (1/2)(\sigma_{bk})^2)\,, \tag{6}$$

$$f_t^{bk} = (1/(\sqrt{2\pi}\bar{\omega}_t^{bk}\sigma_{bk}))exp\left(-(1/2)(\bar{z}_t^{bk})^2\right)\,, \tag{7}$$

$$F_t^{bk} = \Phi(\bar{z}_t^{bk})\,. \tag{8}$$

3.1.2. Retail Deposit Banks

Retail deposit banks have unit mass and are indexed by j. They place homogeneous wholesale deposits $O_t(j)$ in the money market at the policy rate i_t and pay for them by issuing deposit varieties to households $D_t(j)$ and (potentially) stablecoin issuers $D_t^{sc}(j)$. In real aggregate terms, their balance sheet, which has already been substituted in the above equations, is therefore

$$o_t = d_t + d_t^{sc}\,.$$

Retail deposit banks are monopolistically competitive in the market for household and stablecoin issuer deposits, with elasticity of substitution α_t. We allow that the elasticity of substitution between deposit varieties may be affected by competition from stablecoins a_t:[1]

$$\alpha_t = \bar{\alpha} + \phi_\alpha \cdot \frac{a_t}{d_t + a_t}\,. \tag{9}$$

The spread between the policy and deposit rates is then given by

$$\mathfrak{s}_t = \frac{\alpha_t}{\alpha_t + 1}\,, \tag{10}$$

[1]The argument is similar to the theory presented in Drechsler et al. (2017), and is based on the empirical results in Altavilla et al. (2026), who find that stablecoin adoption weakens the deposit channel of monetary policy because stablecoins compete with deposits, effectively decreasing banks' market power.

and the optimal interest rate condition in the market for household deposits becomes[2]

$$r_t^d = \mathfrak{s}_t r_t \,. \tag{11}$$

The interest rate for financial investor deposits is arbitraged with the wholesale deposit rate and therefore with the policy rate. Real retail deposit bank profits Π_t^{rdb} are distributed lump-sum to wholesale banks:

$$\Pi_t^{rdb} = (r_t - r_t^d)\ (d_{t-1} + d_{t-1}^{sc})\ . \tag{12}$$

3.1.3. Retail Lending Banks

Households are the borrowers of retail lending banks. Borrowers have unit mass and are indexed by j. Each borrower uses collateralized bank loans $L_t(j)$ to obtain bank deposits $D_t(j)$, where collateral is a borrower's anticipated annualized sales revenue from production of their variety. Because borrowers cannot make the value of this flow collateral increase by promising a higher level of individual sales revenue, they can only pledge the annualized sales revenue of an average producer multiplied by a haircut parameter κS_t^{mos}, so that total nominal collateral value equals $4\kappa S_t^{mos} P_t y_t$. Here the process S_t^{mos} represents credit supply and therefore money supply shocks

$$\log(S_t^{mos}) = \rho_{mos} \log(S_{t-1}^{mos}) + u_t^{mos}\,.$$

At the beginning of period $t+1$ each individual borrower draws a shock ω_{t+1}^{mod} such that his idiosyncratic collateral value equals $4\kappa S_t^{mos} P_t y_t \omega_{t+1}^{hh}$, where ω_{t+1}^{hh} is a unit mean log-normal random variable distributed independently over time and across borrowers. The standard deviation of $ln(\omega_{t+1}^{hh})$ is $\sigma_{hh,t} = \sigma_{hh} S_t^{risk}$, set when the loan is made, where the process S_t^{risk} represents shocks to borrower risk as in Christiano et al. (2014a), $\log(S_t^{risk}) = \rho_{risk} \log(S_{t-1}^{risk}) + u_t^{risk}$. In the expressions below σ_{hh} stands for $\sigma_{hh,t-1}$. The pdf and cdf of ω_{t+1}^{hh} are $f^{hh}(\omega_{t+1}^{hh})$ and $F^{hh}(\omega_{t+1}^{hh})$.

Each household j receives a loan contract that specifies a nominal loan amount $L_t(j)$, a gross nominal retail rate of interest $i_{r,t}$, payable in $t+1$ if ω_{t+1}^{hh} is sufficiently high to avoid default, and a haircut parameter κS_t^{mos}. Because borrowers are ex-ante identical in terms of their balance sheet ratios, $i_{r,t}$ and κS_t^{mos} are identical across all loans. An important difference to Bernanke et al. (1999) and Christiano et al. (2014a) is that the interest rate $i_{r,t}$ is pre-committed in period t, rather than being determined in period $t+1$ after the realization of time $t+1$ aggregate shocks.[3] The latter assumption ensures zero profits ex-post, while under our debt contract profits are zero ex-ante, but generally differ from zero

[2] See the Online Appendix for the derivations.

[3] See Bernanke et al. (1999): "... conditional on the ex-post realization of R_{t+1}^k, the borrower offers a (state-contingent) non-default payment that guarantees the lender a return equal in expected value to the riskless rate."

ex-post. A borrower j who draws ω_{t+1}^{hh} below a cutoff level $\bar{\omega}_{t+1}^{hh}(j)$ cannot pay the interest rate $i_{r,t}$ and declares bankruptcy, where the ex-post cut-off is given by

$$\bar{\omega}_t^{hh} = \frac{r_t^r \ell_{t-1}}{\kappa S_{t-1}^{mos} r_t^n 4 y_{t-1}}\,, \tag{13}$$

where $r_t^n = 1/\pi_t$. We adopt the notation $f_{t+1}^{hh} = f^{hh}\left(\bar{\omega}_{t+1}^{hh}\right)$ and $F_{t+1}^{hh} = F^{hh}\left(\bar{\omega}_{t+1}^{hh}\right)$.

In the event of bankruptcy, the borrower must hand over the collateral, but the bank can only recover a fraction $(1-\xi)$ of its value, the remainder representing monitoring costs. We denote the lender's gross share and monitoring cost share in pledged capital earnings by $\Gamma_{t+1}(j) = \Gamma(\bar{\omega}_{t+1}^{hh}(j))$ and $\xi G_{t+1}(j) = \xi G(\bar{\omega}_{t+1}^{hh}(j))$.

Banks' zero profit condition states that the unconditional lending rate $i_{r,t}$ is set so that expected earnings net of monitoring costs are sufficient to cover the opportunity cost i_t^ℓ of the loan. There are two equivalent formulations for the zero profit condition. The first is the borrower-specific condition appended to the household optimization problem in Section 3.2.2.:

$$\mathbb{E}_t 4\kappa S_t^{mos} P_t y_t (\Gamma_{t+1}(j) - \xi G_{t+1}(j)) - i_t^\ell L_t(j) = 0\,.$$

The second and aggregate-level formulation is used in the model code to pin down the real retail lending rate:

$$(1 - F_{t+1}^{hh})\frac{r_{t+1}^r}{r_{t+1}^\ell} + (1-\xi) G_{t+1} \frac{\kappa S_t^{mos} r_{t+1}^n 4 y_t}{r_{t+1}^\ell \ell_t} = 1\,. \tag{14}$$

Retail lending banks make net loan losses Λ_t^{rlb} if a larger than anticipated number of households defaults, so that ex-post banks find that they have set their pre-committed retail lending rate at an insufficiently high level:

$$\Lambda_t^{rlb} = r_t^\ell \ell_{t-1} - (\Gamma_t - \xi G_t)\kappa S_{t-1}^{mos} r_t^n 4 y_{t-1}\,. \tag{15}$$

Retail lending banks incur monitoring costs

$$\mathcal{M}_t^{hh} = \xi G_t \kappa S_{t-1}^{mos} r_t^n 4 y_{t-1}\,. \tag{16}$$

Finally, as shown in the Online Appendix, we have the following auxiliary relationships:

$$\bar{\omega}_t^{hh} = exp\left(\bar{z}_t^{hh}\sigma_{hh} - (1/2)(\sigma_{hh})^2\right)\,, \tag{17}$$

$$\Gamma_t = \Phi(\bar{z}_t^{hh} - \sigma_{hh}) + \bar{\omega}_t^{hh}(1 - \Phi(\bar{z}_t^{hh}))\,, \tag{18}$$

$$G_t = \Phi(\bar{z}_t^{hh} - \sigma_{hh})\,, \tag{19}$$

$$\Gamma_t^\omega = 1 - \Phi(\bar{z}_t^{hh})\,, \tag{20}$$

$$G_t^\omega = \bar{\omega}_t^{hh} f_t^{hh}\,, \tag{21}$$

$$f_t^{hh} = (1/(\sqrt{2\pi}\bar{\omega}_t^{hh}\sigma_{hh}))exp\left(-(1/2)(\bar{z}_t^{hh})^2\right)\,, \tag{22}$$

$$F_t^{hh} = \Phi(\bar{z}_t^{hh})\,. \tag{23}$$

3.2. Households

3.2.1. Preferences and Technologies

Households are indexed by j. A representative household maximizes lifetime utility

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t S_t^{sav} \left((1-\nu) S_t^{con} \log(c_t(j) - \nu c_{t-1}) - \frac{\psi}{1+\frac{1}{\eta}} h_t(j)^{1+\frac{1}{\eta}} + \varpi \frac{b_t^{hh}(j)^{1-\vartheta}}{1-\vartheta} \right),$$

where $c_t(j)$ is consumption (with corresponding consumer price index P_t), $h_t(j)$ is hours worked (with corresponding nominal wage W_t), $b_t^{hh}(j)$ is government bonds held by households,[4] ν is external habit, η is the Frisch elasticity, ψ is a scale parameter that determines steady state labor supply, ϑ determines the interest semi-elasticity of demand for government bonds, ϖ is a scale parameter that determines the steady state spread between the interest rates on reserves and on government bonds, and $\beta \in (0,1)$ is the discount factor. Consumers demand an output aggregate y_t that combines individual varieties y_t(j) with elasticity $\epsilon > 1$. The process S_t^{sav} is a shock to saving preferences, and is given by

$$log(S_t^{sav}) = \rho_{sav} log(S_{t-1}^{sav}) + u_t^{sav},$$

while the process S_t^{con} is a shock to consumption demand, and is given by

$$log(S_t^{con}) = \rho_{con} log(S_{t-1}^{con}) + u_t^{con}.$$

Each household produces an output variety $y_t(j)$ using a linear technology in labor $n_t(j)$, $y_t(j) = S_t^{tec} n_t(j)$, where the real wage rate is w_t. The corresponding aggregate production function, which incorporates the labor market clearing condition $n_t = h_t$, is

$$y_t = S_t^{tec} h_t, \tag{24}$$

where the technology shock is

$$\log(S_t^{tec}) = \rho_{tec} \log(S_{t-1}^{tec}) + u_t^{tec}.$$

Households set the price of their variety $P_t(j)$ subject to Rotemberg (1982) price adjustment costs $\Theta_t^p(j) = (\phi_p/2) y_t \left(P_t(j)/P_{t-1}(j) - \bar{\pi}\right)^2$. The corresponding aggregate cost is

$$\Theta_t^p = \frac{\phi_p}{2} y_t \left(\pi_t - \bar{\pi}\right)^2. \tag{25}$$

[4] Government securities have a small but positive convenience yield due to their important role in financial markets (Krishnamurthy and Vissing-Jorgensen, 2012).

3.2.2. Constraints

Household optimization is subject to three constraints, a budget constraint, a money-in-advance constraint, and a bank participation constraint.

Budget Constraint: The nominal interest rate on bank loans $L_t(j)$ is i_t^ℓ, the nominal interest rate on households' bank deposits $D_t(j)$ is i_t^d, the nominal interest rate on stablecoins $A_t(j)$ is i_t^a, and the nominal interest rate on government securities $B_t^{hh}(j)$ is i_t^b. The source of government tax revenue is a proportional tax rate on labor income τ_t^h. Then the household's nominal budget constraint, with associated multiplier $\Lambda_t(j)$, is[5]

$$\begin{aligned}
&P_t c_t(j) + (D_t(j) + A_t(j) + B_t^{hh}(j)) \left(1 + \phi_b \left(b_t^{rat} - \bar{b}_{ss}^{rat}\right)\right) - L_t(j) - P_t \Psi_t^{hh} \\
&= W_t h_t(j)(1 - \tau_t^h) + i_{t-1}^d D_{t-1}(j) + i_{t-1}^a A_{t-1}(j) + i_{t-1}^b B_{t-1}^{hh}(j) \\
&+ P_t(j) y_t(j) - W_t\, n_t(j) - (\phi_p/2) y_t (P_t(j)/P_{t-1}(j) - \bar{\pi})^2 \\
&- \Gamma_t(j) \kappa S_{t-1}^{mos} 4 P_{t-1} y_{t-1}.
\end{aligned}$$

The term $(D_t(j) + A_t(j))\phi_b(b_t^{rat} - \bar{b}_{ss}^{rat})$ represents a transactions cost related to the acquisition of financial assets, where $b_t^{rat} = B_t^{ff}/(4GDP_t) = b_t^{ff}/(4gdp_t)$ is the ratio to GDP of the free float[6] of government debt and $\bar{b}_{ss}^{rat}$ is the corresponding steady state value in the model with government bonds backed stablecoins. This cost is taken as exogenous by households, and the term $P_t \Psi_t^{hh}$ represents its lump-sum distribution back to households. The budgetary effect is therefore neutral, while marginal conditions are affected. This feature allows the model to replicate the small but positive elasticity of equilibrium real interest rates with respect to the free float of government debt found in the empirical literature. Interest rates on all other financial assets are assumed to be affected in the same fashion, so that a change in the government debt-to-GDP ratio, ceteris paribus, will affect the level of interest rates but not the structure of spreads.

Money-in-Advance Constraint: Households need transactions balances to purchase consumption goods. Following Kumhof (2024), we impose a money-in-advance (MIA) constraint with associated multiplier $\Lambda_t(j)\lambda_t^{mia}$, $\varkappa M_t(j) \geq P_t c_t(j)$, where $\varkappa > 0$ is a velocity parameter and $M_t(j)$ is the household's nominal monetary aggregate. The latter is determined by the nominal quantities of bank deposits $D_t(j)$ and stablecoins $A_t(j)$.[7]

[5] See the Online Appendix for full derivations, including the substitutions whereby loan interest charges are substituted out.

[6] The free float is government debt that has to be absorbed by private financial markets, and therefore excludes government debt held on the central bank's balance sheet.

[7] For similar modeling setups, see Barrdear and Kumhof (2022) and Smets et al. (????).

In real aggregate terms, the constraint and the monetary aggregate are

$$\varkappa m_t \geq S_t^{mod} c_t \,, \tag{26}$$

$$m_t = \left(\zeta_t^{\frac{1}{\sigma}} \, d_t^{\frac{\sigma-1}{\sigma}} + (1-\zeta_t)^{\frac{1}{\sigma}} \left(\mathcal{T}_a \, a_t \right)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} , \tag{27}$$

The process S_t^{mod} represents shocks to households' money demand, and is given by

$$log(S_t^{mod}) = \rho_{mod} log(S_{t-1}^{mod}) + u_t^{mod} \,.$$

The term $\zeta_t = \zeta S_t^{scd} / (\zeta S_t^{scd} + 1 - \zeta) \in (0,1)$ represents deposits bias in liquidity, and stays in this range for any value of S_t^{scd}, $\mathcal{T}_a \geq 1$ is the relative payment efficiency of stablecoins, and $\sigma > 0$ is the elasticity of substitution between deposits and stablecoins. The economy without stablecoins cannot be obtained by setting $a_t = 0$ in (27), because the first-order condition for stablecoins becomes singular. In that economy money consists of deposits only, $m_t = d_t$. A key contribution is the introduction of a shock to stable coin demand

$$log(S_t^{scd}) = \rho_z log(S_{t-1}^{scd}) + u_t^{scd}$$

This shock can capture a variety of phenomena, including shifts in crypto-market sentiment[8], regulatory announcements such as MiCA and the GENIUS Act that change the attractiveness of stablecoins or CBDCs, and de-pegging scares such as Terra-Luna type events that trigger a flight from or to stablecoins.

Bank Participation Constraint: The bank participation constraint, with associated multiplier $\Lambda_t(j)\lambda_t^{pc}(j)$, is derived in the Online Appendix. We have

$$\mathbb{E}_t 4\kappa S_t^{mos} P_t y_t (\Gamma_{t+1}(j) - \xi G_{t+1}(j)) - i_t^{\ell} L_t(j) = 0.$$

3.2.3. Optimality Conditions

Let λ_t be the marginal utility of real wealth. Then the first-order conditions for consumption and hours worked are

$$\frac{(1-\nu) S_t^{sav} S_t^{con}}{c_t - \nu c_{t-1}} = \lambda_t \left(1 + \lambda_t^{mia} S_t^{mod} \right) , \tag{28}$$

$$\psi S_t^{sav} (h_t)^{\frac{1}{\eta}} = \lambda_t w_t \left(1 - \tau_t^h \right) . \tag{29}$$

The first-order conditions for deposits, stablecoins and government bonds are

$$1 + \phi_b \left(b_t^{rat} - \bar{b}_{ss}^{rat} \right) - \varkappa \lambda_t^{mia} \left(\frac{\zeta_t m_t}{d_t} \right)^{\frac{1}{\sigma}} = \beta \, \mathbb{E}_t \left(\frac{\lambda_{t+1}}{\lambda_t} r_{t+1}^d \right) , \tag{30}$$

[8]Google Trends shocks are commonly used to identify such shocks, e.g. Altavilla et al. (2026).

$$1+\phi_b\left(b_t^{rat}-\bar{b}_{ss}^{rat}\right)-\varkappa\lambda_t^{mia}\left(\frac{(1-\zeta_t)m_t}{a_t}\right)^{\frac{1}{\sigma}}=\beta\,\mathbb{E}_t\left(\frac{\lambda_{t+1}}{\lambda_t}r_{t+1}^{a}\right), \tag{31}$$

$$1+\phi_b\left(b_t^{rat}-\bar{b}_{ss}^{rat}\right)-\varpi\frac{\left(b_t^{hh}\right)^{-\vartheta}}{\lambda_t}=\beta\,\mathbb{E}_t\left(\frac{\lambda_{t+1}}{\lambda_t}r_{t+1}^{b}\right), \tag{32}$$

Taking the ratio of (30) and (31) and approximating in logs shows that $dlog(d_t)/dlog(r_{t+1}^d) > 0$, where the size of the derivative is increasing in the elasticity of substitution σ. In other words, a higher real deposit rate increases the demand for deposits. Furthermore, and obviously, $dlog(d_t)/dlog(\zeta_t) > 0$. The convenience yields of deposits and stablecoins, after log-approximation, are $log\left(r_{t+1}/r_{t+1}^d\right)=\varkappa\lambda_t^{mia}\left(\partial m_t/\partial d_t\right)$ and $log\left(r_{t+1}/r_{t+1}^a\right)=\varkappa\lambda_t^{mia}\left(\partial m_t/\partial a_t^{sc}\right)$. In words, deposits and stablecoins can pay a lower interest rate than bonds because they provide liquidity services as well as financial returns.

The optimality condition for the bankruptcy cutoff level of productivity is

$$\lambda_t^{pc}=\mathbb{E}_t\frac{\Gamma_{t+1}^{\omega}}{\Gamma_{t+1}^{\omega}-\xi G_{t+1}^{\omega}}, \tag{33}$$

where Γ_{t+1}^{ω} and G_{t+1}^{ω} are the derivatives of Γ_{t+1} and G_{t+1} with respect to $\bar{\omega}_{t+1}^{hh}$. The optimality condition for loans is

$$1=\beta\,\mathbb{E}_t\left(\frac{\lambda_{t+1}}{\lambda_t}\lambda_t^{pc}r_{t+1}^{\ell}\right). \tag{34}$$

Let $m=\epsilon/(\epsilon-1)$, and allow for a shock to price markups S_t^{mup}

$$log(S_t^{mup})=\rho_{mup}log(S_{t-1}^{mup})+u_t^{mup}.$$

Then optimal price setting yields the New Keynesian Phillips curve

$$mS_t^{mup}\,mc_t-1=\phi_p(mS_t^{mup}-1)(\pi_t-\bar{\pi})\pi_t-\beta\phi_p(mS_t^{mup}-1)\mathbb{E}_t\left((\pi_{t+1}-\bar{\pi})\pi_{t+1}\,\frac{\lambda_{t+1}}{\lambda_t}\,\frac{y_{t+1}}{y_t}\right), \tag{35}$$

where real marginal cost is

$$mc_t=\frac{w_t}{S_t^{tec}}. \tag{36}$$

3.3. Stablecoin Issuers

Competitive stablecoin issuers back stablecoins A_t with safe assets. This paper will study three alternatives for backing assets, government bonds B_t^{sc} that earn the positive nominal interest rate i_t^b, bank deposits D_t^{sc} that earn the positive nominal interest rate i_t^d, and central

bank CBDC reserves B_t^{cb} that are assumed to earn no interest, consistent with MiCA and the GENIUS Act. Therefore

$$r_t^a = r_t^n \,, \tag{37}$$

$$r_t^n = 1/\pi_t \,. \tag{38}$$

The balance sheet of stablecoin issuers is

$$a_t = b_t^{sc} + d_t^{sc} + b_t^{cb} \,, \tag{39}$$

where for any of the three regimes one of the right-hand side variables is endogenous while the remaining two are exogenous and equal to zero.

The budget constraint of the stablecoin issuer

$$b_t^{sc} + d_t^{sc} + b_t^{cb} - a_t = r_t^b b_{t-1}^{sc} + r_t^d d_{t-1}^{sc} + r_t^n b_{t-1}^{cb} - r_t^a a_{t-1} - \Pi_t^{sc} - \Pi_t^{cb} \tag{40}$$

determines the profits that are paid out to their owners. Π_t^{sc} are paid out to private owners and are assumed to be consumed by them, so that they enter the aggregate resource constraint. Π_t^{cb} are paid out to the central bank and therefore the government, but due to the assumption that both the stablecoin itself and the backing central bank reserves pay zero interest, this profit will always equal zero.

3.4. Central Bank

The central bank sets the nominal interest rate paid on central bank reserves held by commercial banks, which equals the wholesale rate, by following a Taylor rule

$$i_t = \left(\frac{\bar{\pi}\left(1 + \phi_b\left(\bar{b}^{rat} - \bar{b}_{ss}^{rat}\right) - \varkappa\bar{\lambda}^{mia}\left(\frac{\zeta\bar{m}}{\bar{d}}\right)^{\frac{1}{\sigma}}\right)}{\beta\bar{\mathfrak{s}}} \right)^{(1-\varphi_i)} (i_{t-1})^{\varphi_i} \left(\frac{\pi_t}{\bar{\pi}}\right)^{(1-\varphi_i)\varphi_\pi} S_t^{int}, \tag{41}$$

where the first expression, in large brackets, on the right-hand side is the steady state nominal interest rate. We obtain this by combining the steady state optimality conditions for bank deposits of households and retail deposit banks, where we note that $\bar{b}_{ss}^{rat}$ and $\bar{b}^{rat}$ are the steady state values of the ratios to GDP of the free float of government debt in the model with government-bonds-backed stablecoins and in the model under consideration. The parameter φ_i captures interest rate smoothing, and $\varphi_\pi > 1$ is the inflation feedback coefficient that satisfies the Taylor principle. The monetary policy shock is

$$\log(S_t^{int}) = \rho_{int} \log(S_{t-1}^{int}) + u_t^{int} \,.$$

We also have

$$r_t = i_{t-1}/\pi_t \,. \tag{42}$$

Following a large part of the literature, we do not explicitly model central bank reserves that are held by commercial banks for the purpose of settlement.[9]

[9]Doing so requires a model of multiple banks with heterogenous liquidity needs.

3.5. Government

The real government budget constraint takes account of the fact that the fiscal interest cost of the free float of government debt equals the gross market interest rate i_t^b while the cost of the government that backs interest-free CBDC stablecoins equals zero. We therefore have

$$b_t = r_t^b b_{t-1}^{ff} + r_t^n b_{t-1}^{cb} + g_t - \tau_t^h w_t h_t - \Pi_t^{cb} \,. \tag{43}$$

where total government debt equals

$$b_t = b_t^{hh} + b_t^{sc} + b_t^{cb} \,, \tag{44}$$

while the free float of government debt equals

$$b_t^{ff} = b_t^{hh} + b_t^{sc} \,. \tag{45}$$

The government debt free float debt-to-GDP ratio that is relevant for pricing financial assets is

$$b_t^{rat} = 100 \frac{b_t^{ff}}{4gdp_t} \,, \tag{46}$$

while the total government debt debt-to-GDP ratio that is relevant for stabilizing public finances is

$$b_t^{rat} = 100 \frac{b_t^{ff} + b_t^{cb}}{4gdp_t} \,, \tag{47}$$

with corresponding steady state level $\bar{b}_{ss}^{rat}$.

Government spending g_t equals $\bar{g}$ in steady state and is subject to shocks

$$log(S_t^{gov}) = \rho_{gov} log(S_{t-1}^{gov}) + u_t^{gov} \,,$$

so that

$$g_t = \bar{g} S_t^{gov} \,. \tag{48}$$

The fiscal rule calls for the labor tax rate to adjust to stabilize the debt ratio:

$$\tau_t^h = \bar{\tau}^h + \varphi_b \left(b_{t-1}^{rat} - \bar{b}_{ss}^{rat} \right) , \tag{49}$$

where $\phi_b > 0$ ensures fiscal sustainability.

3.6. Market Clearing

The clearing condition of the market for goods and the definition of GDP are

$$y_t = c_t + g_t + \Pi_t^{sc} + \Theta_t^p \,, \tag{50}$$

$$gdp_t = y_t - \Theta_t^p \,. \tag{51}$$

This condition shows two important leakages from aggregate production y_t, namely consumption of stablecoin issuers Π_t^{sc} and aggregate price adjustment costs Θ_t^p. This shows that handing large stablecoin seigniorage revenue to private issuers, or allowing stablecoin issuance to create more volatile inflation, has direct welfare costs. The labor market clearing condition is

$$n_t = h_t \,,$$

which has already been substituted into all model equilibrium conditions above.

4. Calibration

We calibrate the parameters that govern the steady state of the model based on a combination of guidance from the literature and sample averages for the period 1990Q1-2019Q4. The parameters that are estimated are reported in Section 5..

Real Economy: The real policy rate and the CPI inflation target $\bar{\pi}$ are calibrated at 3% p.a. and 2% p.a. We normalize hours worked to 1. In line with the US sample average, we set the ratio to GDP of government spending to 19.0%. The price gross markup m is fixed at 1.1. The price stickiness parameter ϕ_p and the habit and labor supply elasticity preference parameters ν and η are estimated.

Risk and Regulation: The prior for the minimum capital adequacy ratio γ is centered on 10.5%, which is the sum of the 8.0% Basel III total capital ratio and the 2.5% capital conservation buffer (see Basel Committee on Banking Supervision (2017)). In our model banks hold capital considerably above the regulatory minimum, to self-insure against the risk of violating the MCAR. Based on the data in Federal Reserve Bank of New York (2018), we therefore target an actual steady state capital ratio close to 15.5%, and the estimates imply 15.8%. The share of banks that violate MCAR in any quarter equals 2.5% (based on the frequency of banking crises in Jordà et al. (2011)), and the prior for the borrower bankruptcy rate is centered on 1.5% (based on Ueda and Brooks (2011) and Albanesi et al. (2022)), while its posterior mean is 0.61% per quarter.

Spreads: Spreads relative to the policy rate of wholesale and retail lending rates equal 0.46% (based on AAA commercial paper rates), and 2.35% (based on the maturity-adjusted credit spreads for all listed US non-financial firms in Anderson and Cesa-Bianchi (2024)). These are the values at the prior means; at the posterior mean the two spreads equal 1.56% and 2.34%. The spread of retail deposits equals -1.5% (based on FDIC data but taking into account that our deposits include wholesale as well as retail deposits). The sensitivity of this spread to the quantity of stablecoins is for the time being set to zero. The spread of government bonds equals -0.2% (based on US data). The interest semi-elasticity of household

demand for government bonds with respect to the spread between the policy rate and the rate on government bonds is set to a very high 250, which keeps this spread nearly constant.
Bank Balance Sheets: Based on flow of funds data, the prior for loans is centered on 100% of GDP, and the posterior mean is 100.4%. Together with the capital adequacy ratios, this implies bank net worth and deposits equal to 15.9% and 84.5% of GDP.
Stablecoins: The elasticity of substitution between bank deposits and stablecoins σ is assumed to equal 2 [implied interest semi-elasticity to be computed], while the technological advantage of stablecoins over deposits $\mathcal{T}_a$ is for the time being set to 1. The steady state demand for stablecoins is calibrated at 20% of GDP. The effective price of consumption, which equals the sum of the purchase price and the monetary transaction costs necessary for purchases, equals 10%.
Government and Central Bank: The ratio of total government debt to GDP equals 75%. The elasticity of the risk-free policy rate with respect to a one percentage point increase in the government debt-to-GDP ratio is set to 2 basis points, a conservative assumption by the standards of the IMF's debt sustainability analysis (International Monetary Fund, 2021, 2022). The parameters of the monetary policy rule φ_i and φ_π are estimated. The parameter of the fiscal policy rule is for the time being calibrated at $\varphi_b = 0.01$.

5. Estimation

This section first estimates the stochastic process for stablecoin demand that is used in the simulations, and then the remaining parameters and shock processes. The central object is the process S_t^{scd} in the household liquidity aggregator. In the model, S_t^{scd} shifts the relative liquidity weight on bank deposits and stablecoins. Since the deposit weight ζ_t rises with S_t^{scd}, an increase in stablecoin demand corresponds to a decrease in S_t^{scd}. This sign convention affects the interpretation of impulse responses, but not the estimated persistence or innovation variance of the process.

5.1. Quantity-Based Stablecoin Process

The baseline estimate uses observed quantities of USDT and USDC, the two largest U.S.-dollar stablecoins. Let A_t^{USDT} and A_t^{USDC} denote quarterly end-of-period circulating supply, and define aggregate stablecoin supply as

$$A_t^{SC} = A_t^{USDT} + A_t^{USDC}. \tag{52}$$

Because the level of stablecoin supply is strongly trending over the sample, we estimate the process using stationary transformations rather than raw levels. Our preferred specification

scales aggregate stablecoin supply by M2 and removes a deterministic linear trend:

$$x_t = \log\left(\frac{A_t^{SC}}{M2_t}\right) - (a_0 + a_1 t)\,. \tag{53}$$

We then estimate the quarterly AR(1) process

$$x_t = \rho_{scd} x_{t-1} + \varepsilon_t^{scd}, \qquad \varepsilon_t^{scd} \sim \mathcal{N}(0, \sigma_{scd}^2). \tag{54}$$

This specification is our baseline because it expresses stablecoins relative to a broad dollar liquidity aggregate and avoids interpreting secular market growth as a cyclical stablecoin-demand shock.

Appendix Table 7 reports estimates for the aggregate USDT plus USDC series under alternative stationary transformations. The preferred estimate, based on the detrended log stablecoin-supply-to-M2 ratio, gives

$$\hat{\rho}_{scd} = 0.779, \qquad \hat{\sigma}_{scd} = 0.301. \tag{55}$$

The implied half-life is 2.8 quarters. This estimate is close to the value obtained from detrended log stablecoin supply without the M2 normalization, where $\hat{\rho}_{scd} = 0.805$ and $\hat{\sigma}_{scd} = 0.316$. We therefore set $\rho_{scd} = 0.779$ in the baseline stochastic simulations. The same innovation to S_t^{scd} moves stablecoin balances by different amounts under different backing assets, so we set its size in each regime to match the estimated process: the unconditional standard deviation of log stablecoin balances due to this shock equals $\hat{\sigma}_{scd}/\sqrt{1-\hat{\rho}_{scd}^2} = 0.48$. This gives σ_{scd} equal to 0.930 under government-bond backing, 0.380 under deposit backing and 0.894 under CBDC backing.

5.2. Other Parameters and Shock Processes

The remaining parameters and exogenous processes are estimated by Bayesian methods on U.S. data for the economy without stablecoins, since stablecoins are absent from the sample. We use ten quarterly observables for 1990Q1-2019Q4: the growth rates of real GDP, consumption, hours and credit, PCE inflation, the cycle of the Wu and Xia (2016) shadow policy rate, the Baa corporate spread, the charge-off rate on bank loans, the delinquency rate on bank loans, and the New York Fed flow of household debt into serious delinquency. The spread, the charge-off rate and the flow into delinquency, which is available from 2003, enter in levels and therefore discipline the steady state of the financial block, while the delinquency rate enters in log deviations. These four series carry proxy errors, and the quarters 2008Q3-2010Q4 are treated as missing. The estimated shocks are government spending,

monetary policy, money demand, credit supply, markup, technology and borrower risk. The consumption demand and saving shocks are set to zero.

Table 1 reports the priors and the posterior, based on four chains of 500,000 draws, with a maximum $\widehat{R}$ of 1.001 and a minimum effective sample size of 3,893. The posterior implies a borrower default rate of 0.61% per quarter, close to the 0.58% average flow into serious delinquency, and a loan-loss rate and retail spread of 0.77% and 2.34%, against 0.77% and 2.24% in the data.

Table 1. Prior and Posterior Distributions

Parameter		Type	Prior Mean	Prior s.d.	Posterior Mean	Posterior 5%	Posterior 95%
ν	Habit	Beta	0.650	0.100	0.749	0.693	0.801
η	Frisch elasticity	Gamma	0.500	0.200	0.693	0.573	0.834
ϕ_p	Price adjustment cost	Gamma	2.500	0.500	5.144	3.908	6.451
φ_i	Rate smoothing	Beta	0.750	0.100	0.805	0.763	0.843
φ_π	Inflation response	Normal	1.500	0.250	1.805	1.597	2.039
γ	Minimum capital ratio	Beta	0.105	0.030	0.067	0.037	0.103
ξ	Monitoring cost	Beta	0.210	0.080	0.256	0.231	0.283
σ_{hh}	Borrower risk	Gamma	0.422	0.100	0.271	0.258	0.284
$\bar{z}^{hh}$	Borrower default threshold	Normal	-2.170	0.200	-2.505	-2.531	-2.479
$\ell/(4y)$	Loans to GDP	Normal	1.000	0.100	1.004	0.944	1.064
ρ_{gov}	Government spending	Beta	0.500	0.200	0.904	0.839	0.961
ρ_{int}	Monetary policy	Beta	0.500	0.200	0.254	0.160	0.345
ρ_{mod}	Money demand	Beta	0.500	0.200	0.974	0.960	0.986
ρ_{mos}	Credit supply	Beta	0.500	0.200	0.995	0.990	0.999
ρ_{mup}	Markup	Beta	0.500	0.200	0.993	0.984	0.998
ρ_{tec}	Technology	Beta	0.500	0.200	0.989	0.979	0.997
ρ_{risk}	Borrower risk	Beta	0.500	0.200	0.863	0.820	0.900
σ_{gov}	Government spending	Inv. gamma	0.0100	0.0050	0.0217	0.0194	0.0243
σ_{int}	Monetary policy	Inv. gamma	0.0025	0.0013	0.0014	0.0012	0.0016
σ_{mod}	Money demand	Inv. gamma	0.0100	0.0050	0.0079	0.0070	0.0089
σ_{mos}	Credit supply	Inv. gamma	0.0100	0.0050	0.0124	0.0103	0.0148
σ_{mup}	Markup	Inv. gamma	0.0050	0.0025	0.0206	0.0170	0.0252
σ_{tec}	Technology	Inv. gamma	0.0100	0.0050	0.0060	0.0054	0.0068
σ_{risk}	Borrower risk	Inv. gamma	0.0500	0.0250	0.0197	0.0170	0.0229
σ^{me}_{baa}	Proxy error, Baa spread	Inv. gamma	0.200	0.100	0.563	0.498	0.638
σ^{me}_{co}	Proxy error, charge-offs	Inv. gamma	0.200	0.100	0.200	0.178	0.225
σ^{me}_{del}	Proxy error, delinquency	Inv. gamma	14.000	7.000	5.040	4.083	6.200
σ^{me}_{f90}	Proxy error, flow into 90+	Inv. gamma	0.070	0.035	0.192	0.164	0.224
Implied by the estimates							
Borrower default rate (% per quarter)					0.613	0.569	0.658
Loss given default					0.316	0.291	0.342
Loan-loss rate (% p.a.)					0.774	0.744	0.805
Retail spread (% p.a.)					2.343	2.248	2.440
Collateral scale κ					2.091	1.931	2.258
Penalty coefficient χ					0.017	0.007	0.022
Bank risk σ_{bk}					0.055	0.014	0.091
Bank dividend rate δ_e					0.053	0.039	0.075

Notes: Posterior from four chains of 500,000 draws. $\bar{z}^{hh}$ is the threshold whose normal cdf equals the borrower default rate. Implied quantities are posterior means and 90% bands of the derived parameters and steady-state levels. Consumption demand, saving and stablecoin demand shocks are not part of the estimated block.

The model writes each non-policy shock in the form

$$\log S^x_t = \rho_x \log S^x_{t-1} + \varepsilon^x_t, \qquad \varepsilon^x_t \sim N(0, \sigma^2_x),$$

so the standard deviations in Table 2 are innovation standard deviations in log points, except

for the monetary policy shock, which enters the Taylor-rule residual. Table 2 sets out the resulting processes. The credit supply, markup and technology processes are all very persistent, with autoregressive coefficients above 0.98. For the real and nominal macro shocks, the main comparison is Smets and Wouters (2007), who estimate a medium-scale U.S. DSGE model with technology, government-spending, preference, markup, and monetary policy shocks. Their posterior estimates imply very persistent technology and fiscal disturbances, somewhat lower but still substantial persistence for demand and markup disturbances, and a small monetary policy innovation. For the credit-supply wedge and borrower risk, we use Christiano et al. (2014b) as the benchmark, since their financial-accelerator DSGE model estimates a persistent risk shock and finds that financial-risk fluctuations are quantitatively important for U.S. business-cycle volatility. For the money-demand wedge, the comparison is the money-in-utility/New Keynesian evidence in Ireland (2004) and related work, which treats liquidity demand as persistent and empirically volatile.

Table 2. Baseline Exogenous Shock Processes

Shock	Persistence	Std. dev.	Baseline value	Comparison
Consumption demand	ρ_{con}	σ_{con}	0.90, 0.025	Not estimated; impulse responses only. Preference/risk-premium shock in Smets and Wouters (2007).
Government spending	ρ_{gov}	σ_{gov}	0.904, 0.0217	Highly persistent fiscal shock in Smets and Wouters (2007).
Money demand	ρ_{mod}	σ_{mod}	0.974, 0.0079	Persistent liquidity-demand disturbances as in Ireland (2004).
Credit supply	ρ_{mos}	σ_{mos}	0.995, 0.0124	Persistent financial/risk shock in Christiano et al. (2014b).
Borrower risk	ρ_{risk}	σ_{risk}	0.863, 0.0197	Risk shock in Christiano et al. (2014b).
Markup	ρ_{mup}	σ_{mup}	0.993, 0.0206	Price-markup shock in Smets and Wouters (2007).
Technology	ρ_{tec}	σ_{tec}	0.989, 0.0060	TFP shock in Smets and Wouters (2007).
Monetary policy	ρ_{int}	σ_{int}	0.254, 0.0014	Policy innovation in the Taylor rule.
Stablecoin demand	ρ_{scd}	σ_{scd}	0.779, by regime	Matched to the USDT+USDC supply process relative to M2.

Notes: Each cell in the baseline-value column reports (ρ, σ), at the posterior mean of Table 1 unless otherwise stated. The macro-shock standard deviations are in the units of the corresponding model wedges, and are therefore not directly comparable with those in the cited papers, whose shock normalizations differ. The stablecoin-demand persistence is estimated, and the size of its innovation in each regime is reported, in Section 5.1..

5.3. Estimation Procedure and Diagnostics

We estimate the model by Bayesian methods, following Smets and Wouters (2007), An and Schorfheide (2007) and Herbst and Schorfheide (2016), combining the likelihood, computed with the Kalman filter (Durbin and Koopman, 2012), with the priors in Table 1. The model is

solved to first order around an analytical steady state that is recomputed for each parameter vector, with κ, σ_{bk}, χ and δ_e derived from the estimated parameters and the calibrated targets. The Kalman filter treats the masked quarters, and the quarters before the flow into delinquency becomes available, as missing observations, and the first four quarters only initialize the filter.

We locate the posterior mode with a global optimizer (CMA-ES, Hansen et al. 2003) followed by two runs of a gradient-based optimizer (csminwel), from dispersed starting points, and we restart the search from each point at which it stops. We then sample from the posterior with four chains of the random-walk Metropolis-Hastings algorithm (Schorfheide, 2000), using a proposal covariance proportional to the inverse Hessian at the mode. One chain starts at the mode and the other three start from dispersed draws. Each chain has 500,000 draws, of which the first half is discarded.

Table 3 reports the main diagnostics and the criterion for each. Additional diagnostics, covering the search for multiple modes, Geweke tests, collinearity among the remaining parameters, robustness to the sample and the data, and a comparison of model-implied and data volatility, are reported in Appendix C. The first three concern the mode. Identification strength is the size of each parameter relative to its asymptotic standard error, and collinearity measures how far the effect of a parameter on the moments of the observables can be reproduced by the other parameters (Iskrev, 2010; Ratto and Iskrev, 2011). The Hessian should be positive definite at the mode (An and Schorfheide, 2007), and the log posterior, profiled along each parameter, should peak at the mode (Adjemian et al., 2024). The next three concern the sampler: the acceptance rate of the proposal (Roberts et al., 1997), the potential scale reduction factor $\widehat{R}$ of Gelman and Rubin (1992) across chains, and the effective sample size after allowing for the autocorrelation of the draws (Geyer, 1992). The last three concern the economics. A parameter is flagged as dominated by its prior if its posterior standard deviation is close to its prior standard deviation while its mean barely moves (Canova and Sala, 2009; Koop et al., 2013). The smoothed shocks, standardized by their estimated standard deviations, should contain no extreme outliers (Cúrdia et al., 2014), and no single shock should dominate the historical decomposition of any observable (Smets and Wouters, 2007).

Table 3. Estimation Diagnostics

Diagnostic	Criterion	Result	Source
Identification strength	at least 2	minimum 2.04 (ρ_{int})	Iskrev (2010)
Collinearity of financial parameters	below 0.99	maximum 0.98 (γ)	Ratto and Iskrev (2011)
Hessian at the mode	positive definite	all converged searches	An and Schorfheide (2007)
Posterior profiles	peak at the mode	28 of 28 parameters	Adjemian et al. (2024)
Acceptance rate	20% to 35%	30.3% to 30.5%	Roberts et al. (1997)
$\widehat{R}$	at most 1.01	maximum 1.0007	Gelman and Rubin (1992)
Effective sample size	at least 400	minimum 3,893	Geyer (1992)
Parameters dominated by their prior	none	none	Koop et al. (2013)
Largest standardized smoothed shock	at most 6	3.90	Cúrdia et al. (2014)
Largest single-shock share	at most 80%	49.7%	Smets and Wouters (2007)

Notes: A parameter is flagged as dominated by its prior if the ratio of posterior to prior standard deviation exceeds 0.8 and its mean moves by less than 0.5 prior standard deviations. Smoothed shocks exclude the masked quarters. The source column gives the origin of each test or, for the last two rows, of the object examined. The criteria for $\widehat{R}$ and the effective sample size follow the recommendations of Vehtari et al. (2021) for their rank-normalized statistics; the other criteria are our own.

On these criteria the estimation performs well: the chains mix well, the posterior peaks at the mode, and the data move every parameter away from its prior or tighten it. For additional diagnostics, see Appendix C.

6. Simulation Results

This section reports moments from the stochastic model at the posterior mean of Table 1. For each backing regime and for the economy without stablecoins, the model is solved to first order with all estimated shocks and the stablecoin-demand shock active, the latter sized in each regime as in Section 5.1.. Standard deviations are expected values over samples of 120 quarters, the length of the estimation sample, because several of the estimated processes are close to a unit root. We focus on four outcome variables: stablecoin seigniorage as a share of GDP, annualized inflation, a consumption-equivalent welfare measure, and GDP. We also report the share of variance attributable to the stablecoin-demand shock, because this directly measures the contribution of the additional portfolio-demand disturbance introduced by stablecoins.

The seigniorage variable is Π_t^{sc}/GDP_t, expressed in percentage points. Inflation is annualized as $400\log(\pi_t)$. At first order the means are steady-state values, so the means of consumption and GDP are percentage differences from the steady state of the no stablecoin

economy, while their standard deviations refer to percentage deviations from each regime's own steady state. The welfare statistic CCV is computed as the percent change in consumption, relative to the no stablecoin economy, that delivers the same welfare level.

6.1. Moments

Table 4 reports the main simulated moments. The steady-state seigniorage ranking is sharp. CBDC-backed stablecoins generate no private seigniorage because the stablecoin and the backing central-bank liability both pay zero interest. Deposit-backed and government-bond-backed stablecoins generate positive private seigniorage, with the government-bond-backed regime producing the larger mean seigniorage flow. This supports the main steady-state message of the paper: private stablecoin issuance redistributes revenue away from the public sector and therefore ultimately from households unless the backing asset is a non-interest-bearing central-bank liability.

Inflation equals the two percent target on average in all regimes. Inflation volatility, however, differs across backing structures. In the current simulations all three stablecoin regimes have lower inflation volatility than the economy without stablecoins. Among them the deposit-backed regime has the lowest, while the government-bond-backed regime has the highest. GDP and consumption volatility display a different ranking: they are slightly higher with stablecoins, with the exception of GDP under deposit backing, and deposit backing is the least volatile of the three regimes. The CCV statistic is normalized relative to the economy without stablecoins. Relative to this benchmark, the government-bond-backed regime has mean $CCV = -1.379$ and the deposit-backed regime has mean $CCV = -0.822$, while the CBDC-backed regime has a small gain, with mean $CCV = 0.392$, because it reduces the interest cost of government financing.

Table 4 therefore supports the paper's steady-state seigniorage ranking. CBDC-backed stablecoins generate no private stablecoin seigniorage; deposit-backed stablecoins generate positive private seigniorage; and government-bond-backed stablecoins generate the largest private seigniorage flow. The same table is more cautious on the volatility message. Its volatility rows combine all shocks, including a stablecoin-demand shock that is present only in the stablecoin regimes, so they do not by themselves establish whether stablecoins reduce volatility relative to a world without stablecoins. That claim requires the breakdown by source of shocks in Section 6.3. and the shock-by-shock IRFs.

Table 4. Simulated Moments by Stablecoin Backing Regime

Moment	No stablecoins	Government-bond-backed	Deposit-backed	CBDC-backed
Seigniorage mean	0.000	0.961	0.702	0.000
Seigniorage sd	0.000	0.512	0.491	0.000
Inflation mean	2.000	2.000	2.000	2.000
Inflation sd	5.579	4.563	2.872	4.152
Consumption mean	0.000	-1.072	-0.900	-0.258
Consumption sd	6.733	7.207	6.878	7.190
GDP mean	0.000	0.093	-0.027	-0.209
GDP sd	5.474	5.736	5.441	5.784
CCV mean	0.000	-1.379	-0.822	0.392

Notes: Seigniorage is stablecoin issuer profit as a percent of GDP. Inflation is annualized in percent. Means are steady-state values, with consumption and GDP in percent of their no stablecoin steady states. Standard deviations are expected values over samples of 120 quarters, with consumption and GDP in percentage deviations from steady state. CCV is reported as a consumption-equivalent percentage relative to the non-stablecoin economy. Appendix C compares model-implied and data standard deviations.

6.2. Role of the Stablecoin-Demand Shock

The additional shock introduced by stablecoins is the shock to the relative demand for stablecoins and deposits. Its contribution to volatility is reported in Table 5. The results show that the stablecoin demand shock matters most for the quantity of stablecoins itself, accounting for more than four fifths of the variance of stablecoin balances under government-bond and CBDC backing and about half under deposit backing. It also explains a nontrivial share of GDP and consumption volatility, and most of inflation volatility, in the government-bond and CBDC regimes. This reflects the large size of the stablecoin-demand process relative to the estimated macro shocks.

The deposit-backed regime is different. In that regime, stablecoin-deposits demand shifts can be accommodated very flexibly by issuing or retiring stablecoins against bank deposits. As a result, the stablecoin-demand shock explains very little of GDP, consumption, and inflation volatility, even though it still accounts for a meaningful share of the variance of stablecoin balances and seigniorage. This result supports this paper's message, which we will re-encounter in our analysis of impulse responses, that deposit backing is the most stabilizing backing structure for portfolio-demand shocks, while government-bond and CBDC backing are destabilizing.

Table 5. Variance Share Attributable to the Stablecoin-Demand Shock

Moment	Government-bond-backed	Deposit-backed	CBDC-backed
GDP	8.668	0.045	8.672
Consumption	6.456	0.273	8.561
Inflation	89.621	2.069	87.866
Seigniorage	88.633	45.700	–
Stablecoin balances	86.631	48.304	86.571

Notes: Entries report percent of the expected variance over 120 quarters attributable to E_t^{scd}. The CBDC-backed seigniorage variance share is undefined because private stablecoin seigniorage is identically zero in that regime.

6.3. Volatility by Source of Shocks

Table 6 separates volatility by the source of the shocks. Financial shocks are absorbed by stablecoins: their contribution to inflation volatility falls from 4.87 in the economy without stablecoins to 0.72 and 0.70 under government-bond and CBDC backing and to 2.28 under deposit backing, and their contribution to GDP volatility falls from 1.81 to 0.25, 0.24 and 0.91. Monetary policy shocks are also dampened. Real shocks are slightly amplified, with their contribution to GDP volatility rising from 5.15 to 5.47, 5.52 and 5.35, although their contribution to inflation volatility falls. Stablecoin-demand shocks add volatility, far more under government-bond and CBDC backing than under deposit backing.

Table 6. Volatility by Source of Shocks

Source of shocks	No stablecoins	Government-bond-backed	Deposit-backed	CBDC-backed
GDP				
Financial	1.810	0.249	0.911	0.235
Monetary policy	0.361	0.253	0.318	0.292
Real	5.153	5.470	5.354	5.515
Stablecoin demand	–	1.689	0.116	1.703
Consumption				
Financial	2.235	0.377	0.868	0.291
Monetary policy	0.445	0.372	0.425	0.360
Real	6.336	6.950	6.800	6.860
Stablecoin demand	–	1.831	0.360	2.104
Inflation				
Financial	4.867	0.715	2.278	0.704
Monetary policy	1.875	1.206	1.363	1.185
Real	1.981	0.443	1.013	0.438
Stablecoin demand	–	4.319	0.413	3.892

Notes: Entries report the standard deviation due to each group of shocks alone, expected over samples of 120 quarters. Financial shocks are credit supply, money demand and borrower risk; real shocks are technology, markup and government spending. GDP and consumption are in percentage deviations from steady state, and inflation is annualized in percentage points.

6.4. Sensitivity to the Stablecoin Share

In Figure 1 we compare our four economies, an economy without stablecoins, an economy with government-debt-backed stablecoins, an economy with deposit-backed stablecoins, and an economy with CBDC-backed stablecoins. In this figure the x-axis represents ζ_*, which represents stablecoin balances in percent of money balances, varied between 1% and 50%. At each value of ζ_* we re-solve the steady state of the model by changing the liquidity weight ζ, while holding collateral coverage, the government bond spread and the total debt ratio at their baseline targets, and we then solve the model to first order.

Seigniorage losses rise almost linearly with the stablecoin money share for government-debt-backed and deposit-backed stablecoins, reaching 2.03% and 1.48% of GDP at a share of 50%, with corresponding CCV means of -3.07% and -1.87%. The economy without stablecoins and the CBDC-backed stablecoin economy have zero private seigniorage income by construction, and the CBDC-backed economy has a CCV gain that rises to 0.73%. Since the stablecoin-demand process is estimated on percentage changes in stablecoin supply, the size of its innovation is adjusted with ζ so that its effect on the percentage change in stablecoin demand remains as in the baseline.

In the four subplots, the black line for the economy without stablecoins is held fixed as the benchmark, while the three stablecoin economies are re-solved at each value of ζ_*. Under

government-debt and CBDC backing, inflation volatility first falls with the stablecoin share and then rises, exceeding that of the economy without stablecoins above a share of roughly 30% to 35%. Under deposit backing it remains below that benchmark throughout.

6.5. Interpretation

The results point to a trade-off across backing regimes. Government-bond-backed stablecoins generate the largest private seigniorage transfer, making them least attractive from the standpoint of public revenue and therefore ultimately of private consumption. Deposit-backed stablecoins generate smaller private seigniorage incomes and the lowest overall GDP and inflation volatility in the current simulations, because they absorb stablecoin-demand shocks, although they dampen financial shocks the least. CBDC-backed stablecoins eliminate private seigniorage and have the highest CCV. Their volatility performance is close to that of government-bond-backed stablecoins.

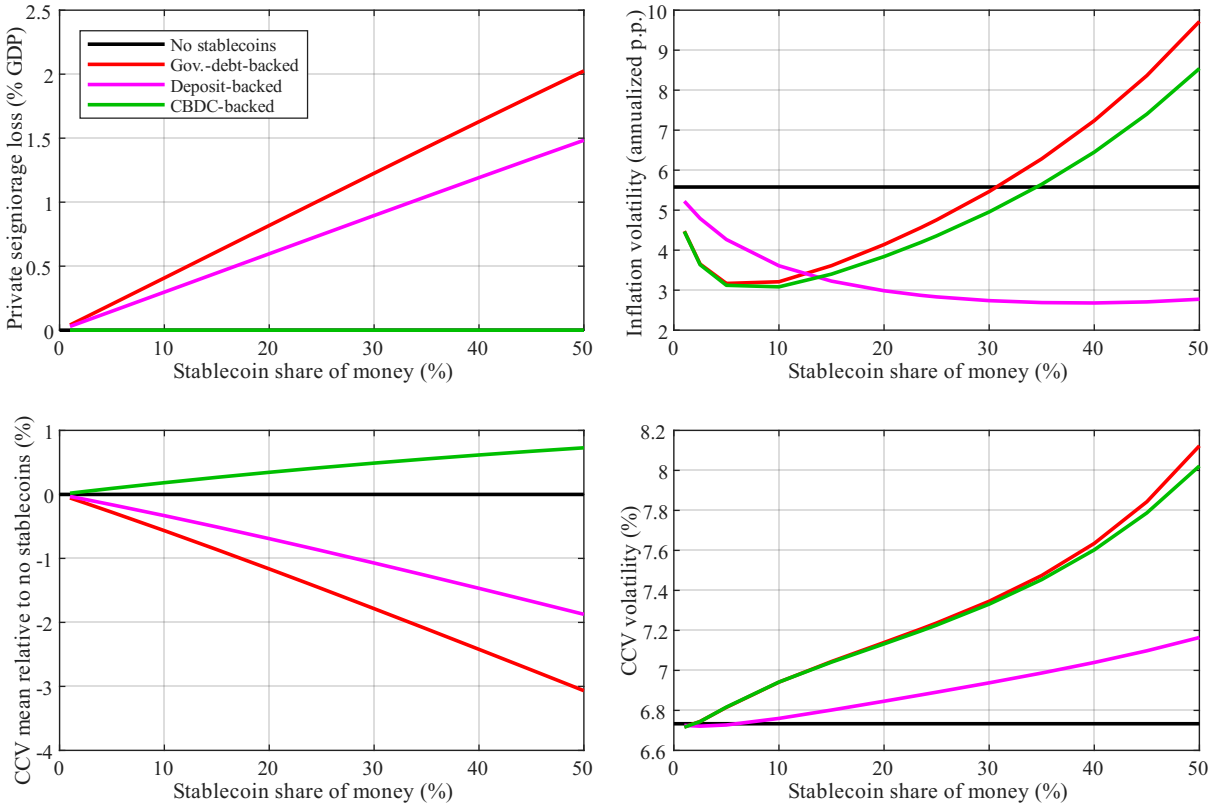


Figure 1. ζ_* sensitivity analysis. The horizontal axis varies stablecoin balances from 1 to 50 percent of money balances, with the model re-solved at each point. The black line denotes the economy without stablecoins, the green line denotes CBDC-backed stablecoins, the pink line denotes deposit-backed stablecoins, and the red line denotes government-debt-backed stablecoins.

The variance decomposition also shows why the source of shocks matters. For shocks to the relative demand for stablecoins, deposit backing is stabilizing because issuance can be absorbed directly through the banking system. For the overall welfare ranking, however, this stabilizing role must be weighed against seigniorage redistribution and against the effects of financial, monetary, and real shocks. This is why the final ranking is an empirical question: it depends on the relative importance of the different structural shocks in the data. At the estimated parameters, real shocks account for most of the volatility of GDP and consumption, which stablecoins raise only slightly, while financial and monetary shocks account for most of the volatility of inflation, which stablecoins reduce, although stablecoin-demand shocks offset part of this reduction under government-bond and CBDC backing.

7. Impulse Responses

7.1. Financial Shocks

In this subsection we will obtain two key results. First, under financial shocks that require balance sheet adjustments, the presence of stablecoins provides an additional option for such adjustments. It therefore serves as a useful shock absorber that reduces output and inflation volatility relative to an economy without stablecoins. Second, among the differernt backing options for stablecoins, the CBDC-backed and government-debt-backed options are most effective in response to shock to aggregate money supply and money demand shocks, while the deposit-backed option is most effective in response to shocks to the demand for relative quantities of stablecoins and deposits.

7.1.1. Credit Supply Shock

Figure (2) shows an impulse response to an expansionary shock to banks' credit supply, specifically a decrease in the haircut or an increase in S_t^{mos} that increases banks' willingness to lend against the same collateral.

In the economy without stablecoins the shock leads to a simultaneous increase in loans and deposits. The increase in deposits, through more abundant liquidity that is reflected in a reduction in the monetary wedge, facilitates an increase in consumption demand that in turn increases output and inflation.

These effects on the real economy are far smaller in economies with stablecoins. This is because households now have an additional option for responding to the increases in liquidity, namely reducing their holdings of stablecoins. This is least effective with deposits-backed stablecoins, with output and inflation effects still roughly half as large as in the economy without stablecoins, because in this case the liquidation of stablecoin holdings releases deposits to the market that need to be reabsorbed by households. By contrast, under the government-securities-backed and CBDC-backed alternatives the reduction in stablecoin holdings results in government securities being released to the market, either by the stablecoin issuer or by the central bank, and being reabsorbed by households without thereby increasing liquidity. In this case the effects of the credit supply shock on real activity and inflation are far smaller than in the economy without stablecoins.

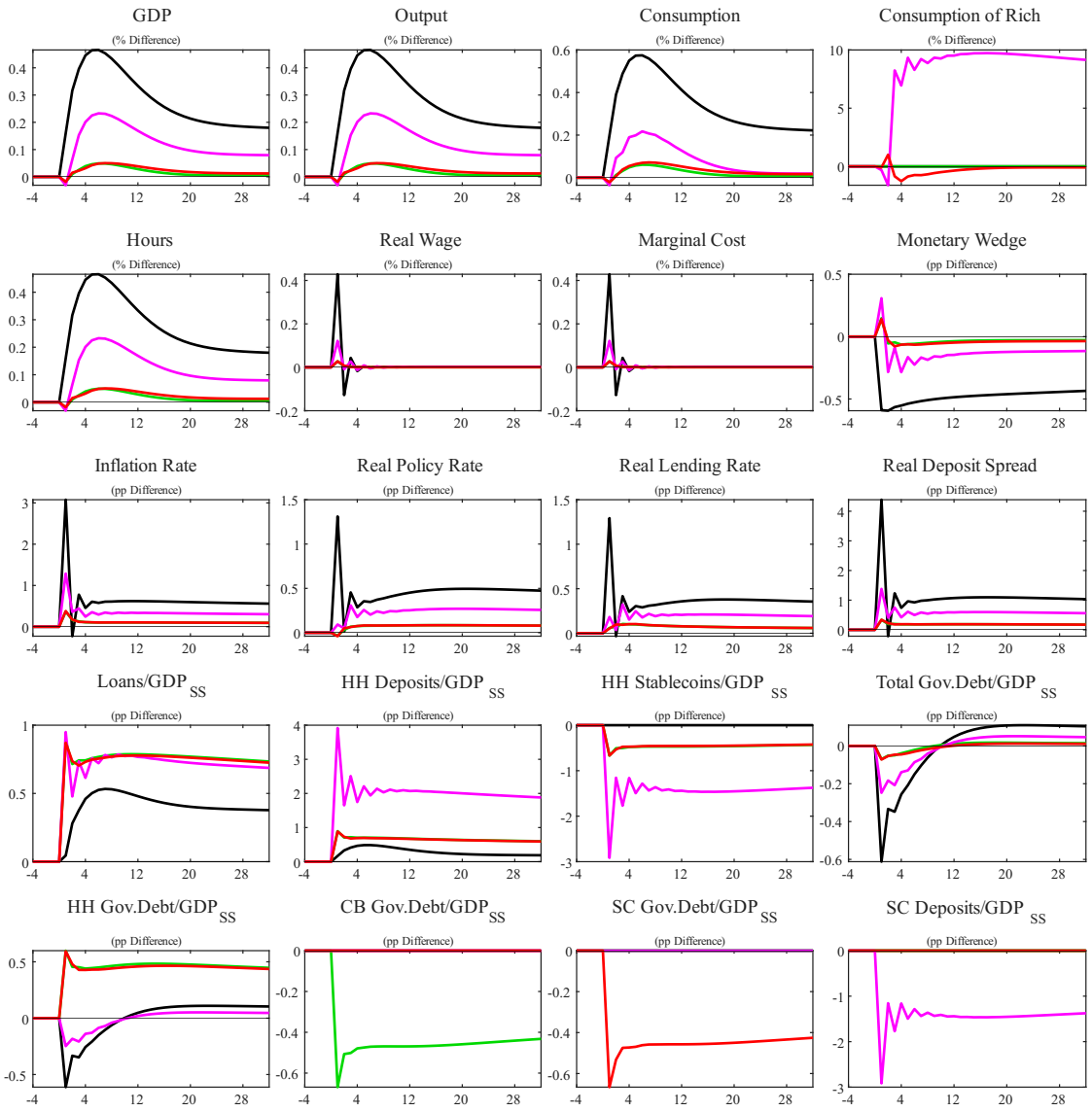


Figure 2. Credit Supply Shock. One-standard-deviation shock at the posterior mean. Horizontal axis in quarters, shock at $t = 1$. Lines for the economy without stablecoins are in black, for CBDC-backed stablecoins in green, for deposit-backed stablecoins in pink, and for government-debt-backed stablecoins in red.

7.1.2. Money Demand Shock

Figure (3) shows an impulse response to an expansionary shock to households' money demand, specifically an increase in money velocity or a decrease in S_t^{mod} that makes a given quantity of money circulate faster, thereby reducing the need for liquidity while stimulating real activity.

In the economy without stablecoins the shock leads to a simultaneous decrease in loans and deposits. However, despite this the monetary wedge decreases so that output and inflation

increase.

The effects on the real economy are again significantly smaller in economies with stablecoins because households reduce their holdings of liquidity partly through a reduction in holdings of stablecoins. And again this is least effective with deposits-backed stablecoins because the liquidation of stablecoin holdings releases deposits to the market that need to be reabsorbed by households. Under the government-securities-backed and CBDC-backed alternatives the reduction in stablecoin holdings results in government securities rather than bank deposits being released to the market. The effects of the money demand shock on real activity and inflation are therefore far smaller than in the economy without stablecoins.

7.1.3. Borrower Risk Shock

Figure (4) shows an impulse response to an increase in borrower risk S_t^{risk}. In the economy without stablecoins the shock reduces loans and deposits and raises the monetary wedge, so that output and inflation decrease. As for the other financial shocks, households can offset part of the loss of liquidity by raising their holdings of stablecoins. The effects on the real economy are therefore far smaller in economies with stablecoins, and smallest under the government-securities-backed and CBDC-backed alternatives.

7.1.4. Stablecoin Demand Shock

Figure (5) shows an impulse response to a shock to households' stablecoin demand, specifically an increase in the demand for stablecoins relative to bank deposits or a decrease in S_t^{scd}.

This shock is of course not present in the economy without stablecoins. However, among the three stablecoin regimes the ranking is now reversed, with deposit-backed stablecoins yielding the greatest stability in output and inflation while the two alternatives produce significant fluctuations. The reason is of course that when household wish to increase their holdings of stablecoins and reduce their holdings of deposits, this can be directly accommodated through the issuance of new stablecoins against deposits. By contrast, in the other two regimes, the reduction in deposits remains far smaller, so that total liquidity rises, and the shock therefore leads to an increase in real activity and inflation.

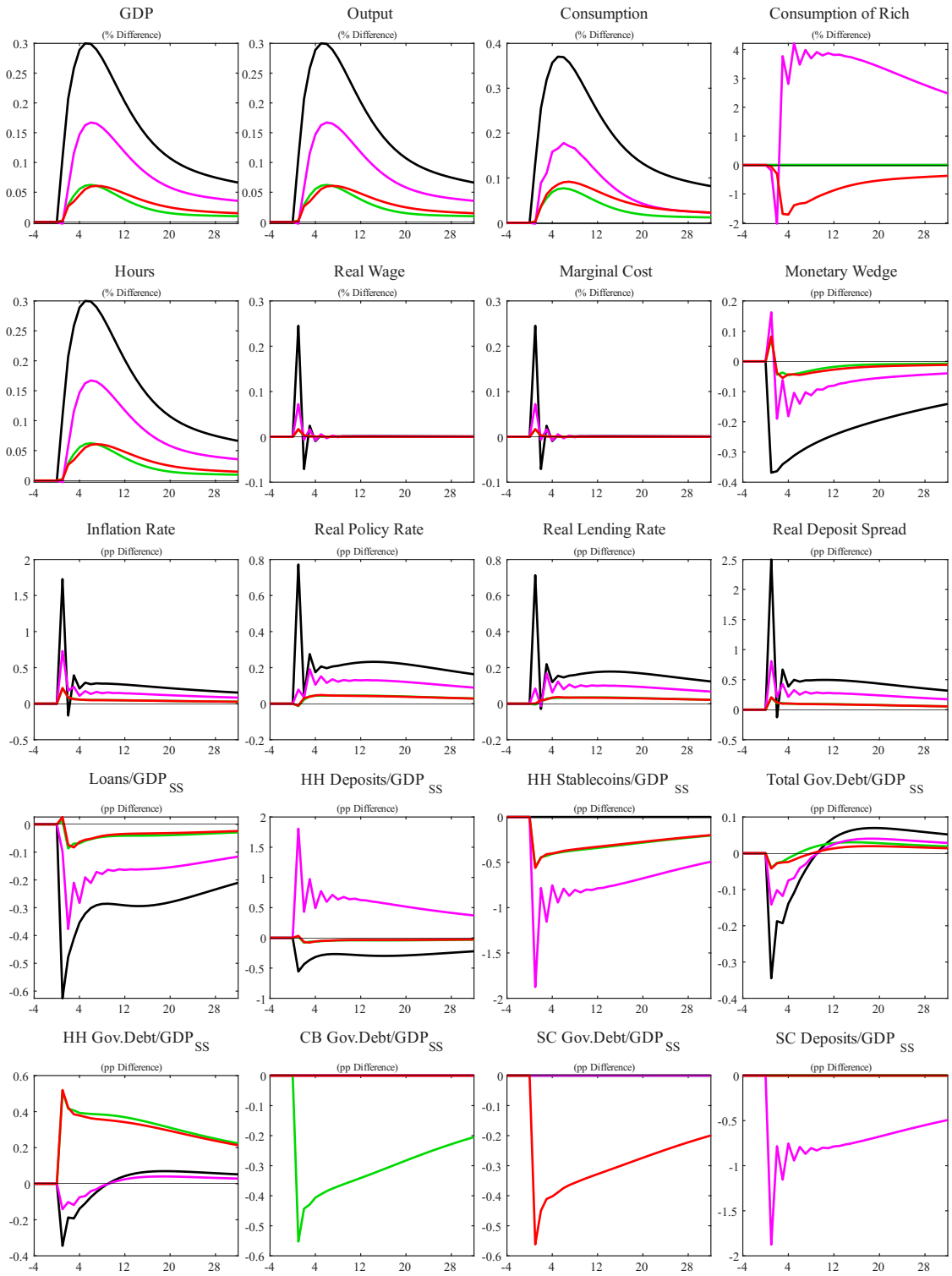


Figure 3. Money Demand Shock. One-standard-deviation shock at the posterior mean. Horizontal axis in quarters, shock at $t = 1$. Lines for the economy without stablecoins are in black, for CBDC-backed stablecoins in green, for deposit-backed stablecoins in pink, and for government-debt-backed stablecoins in red.

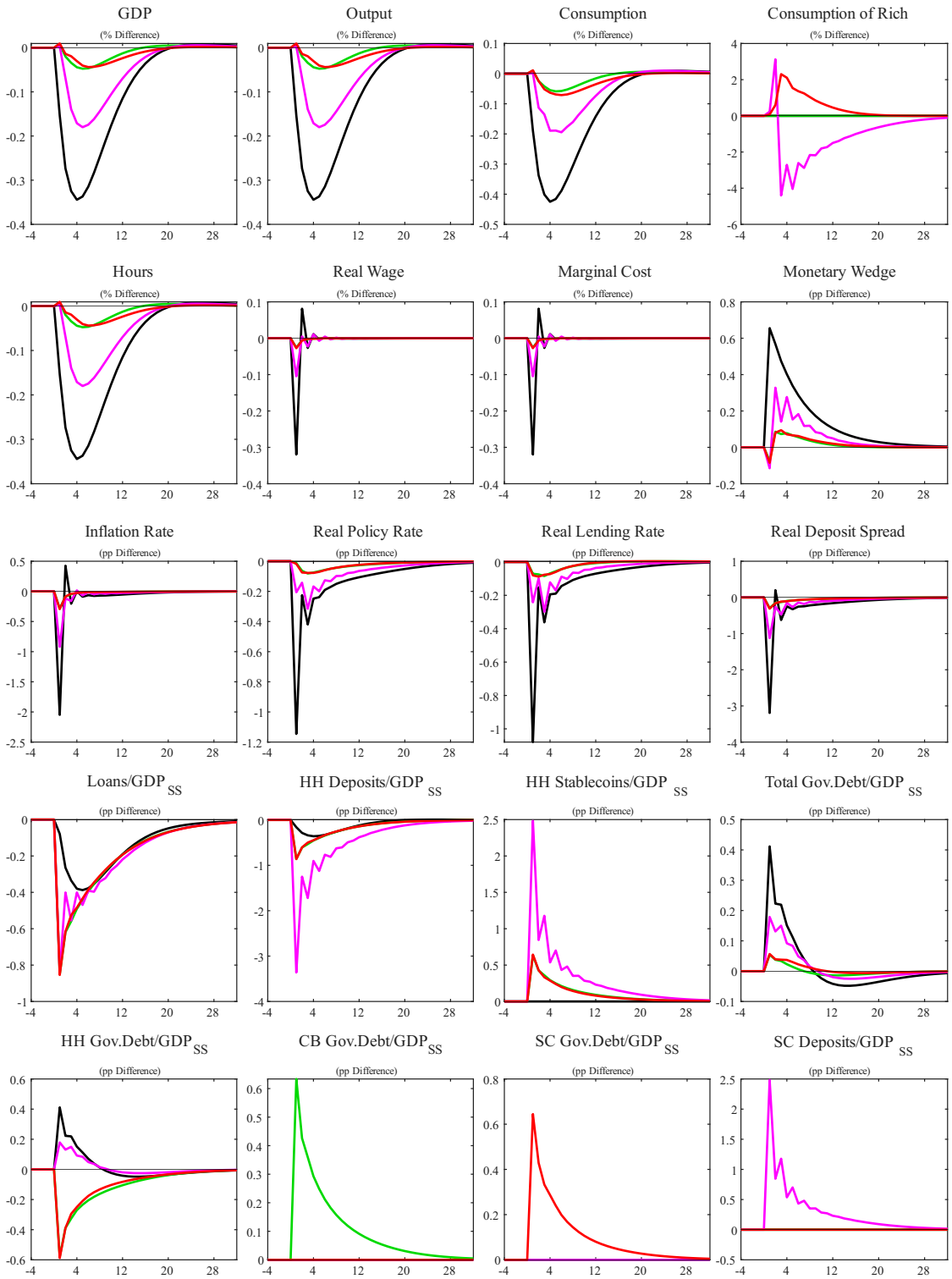


Figure 4. Borrower Risk Shock. One-standard-deviation shock at the posterior mean. Horizontal axis in quarters, shock at $t = 1$. Lines for the economy without stablecoins are in black, for CBDC-backed stablecoins in green, for deposit-backed stablecoins in pink, and for government-debt-backed stablecoins in red.

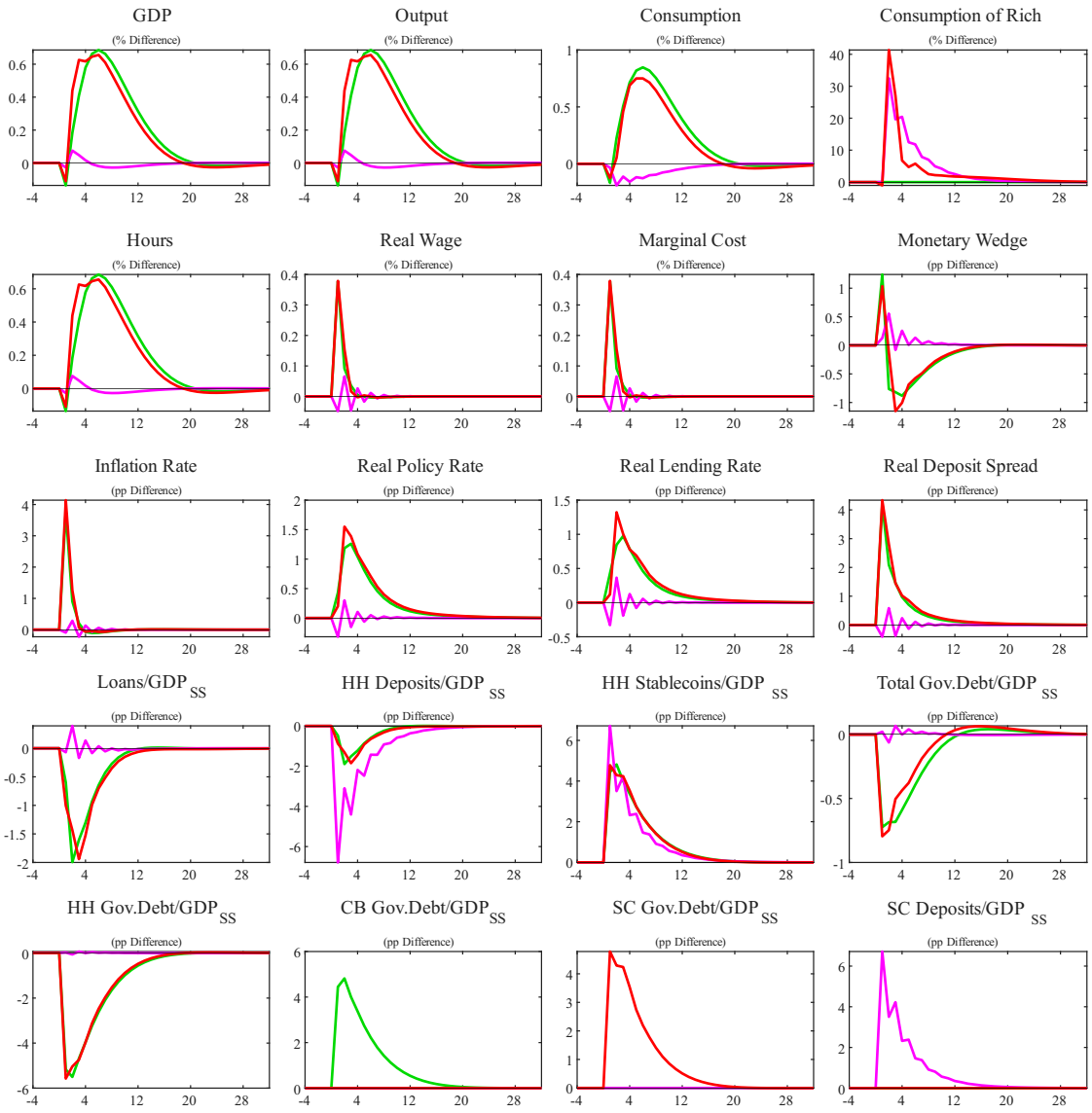


Figure 5. Stablecoin Demand Shock. One-standard-deviation shock, sized in each regime as in Section 5.1.. Horizontal axis in quarters, shock at $t = 1$. Lines for the economy without stablecoins are in black, for CBDC-backed stablecoins in green, for deposit-backed stablecoins in pink, and for government-debt-backed stablecoins in red.

7.2. Real Shocks

7.2.1. Consumption Demand Shock

Figure (6) shows an impulse response to an expansionary shock to households' consumption demand, specifically an increase in S_t^{con}. This shock is not part of the estimated shock set, and it is shown for comparison.

This shock increases real consumption demand, which in turn increases money demand that households satisfy through a combination of additional deposits and stablecoins. In

an economy without stablecoins households can satisfy this demand through increased bank borrowing and bank deposits, which is elastically provided by banks. Under CBDC-backed or government-debt-backed stablecoins the response is even more elastic because households can also use their holdings of bonds to obtain additional stablecoins, and as a result the fluctuations in output, consumption and hours are even more pronounced. By contrast, under a deposits-backed stablecoin the only way to obtain both more bank deposits and more stablecoins is to borrow even more heavily from banks, and this constrains the increase in real activity. For this shock stablecoins therefore amplify the shock rather than moderating its effects, least so under the deposits-backed option.

7.2.2. Government Spending Shock

Figure (7) shows an impulse response to an expansionary shock to the government's demand for output, specifically an increase in S_t^{gov}. The main observation is that, unlike for the consumption demand shock, the effect on output is moderated in all three stablecoin regimes, while the crowding out of consumption is larger.

7.2.3. Technology Shock

Figure (8) shows an impulse response to an expansionary technology shock, specifically an increase in S_t^{tec}. Again, similar to the consumption demand shock and for the same reasons, CBDC-backed and government-debt-backed stablecoins slightly amplify the effects of the shock while deposits-backed stablecoins amplify them less.

7.2.4. Markup Shock

Figure (9) shows an impulse response to an increase in the price markup S_t^{mup}. The shock reduces output and raises inflation. As for the technology shock, stablecoins slightly amplify the effect on output, while they moderate the effect on inflation.

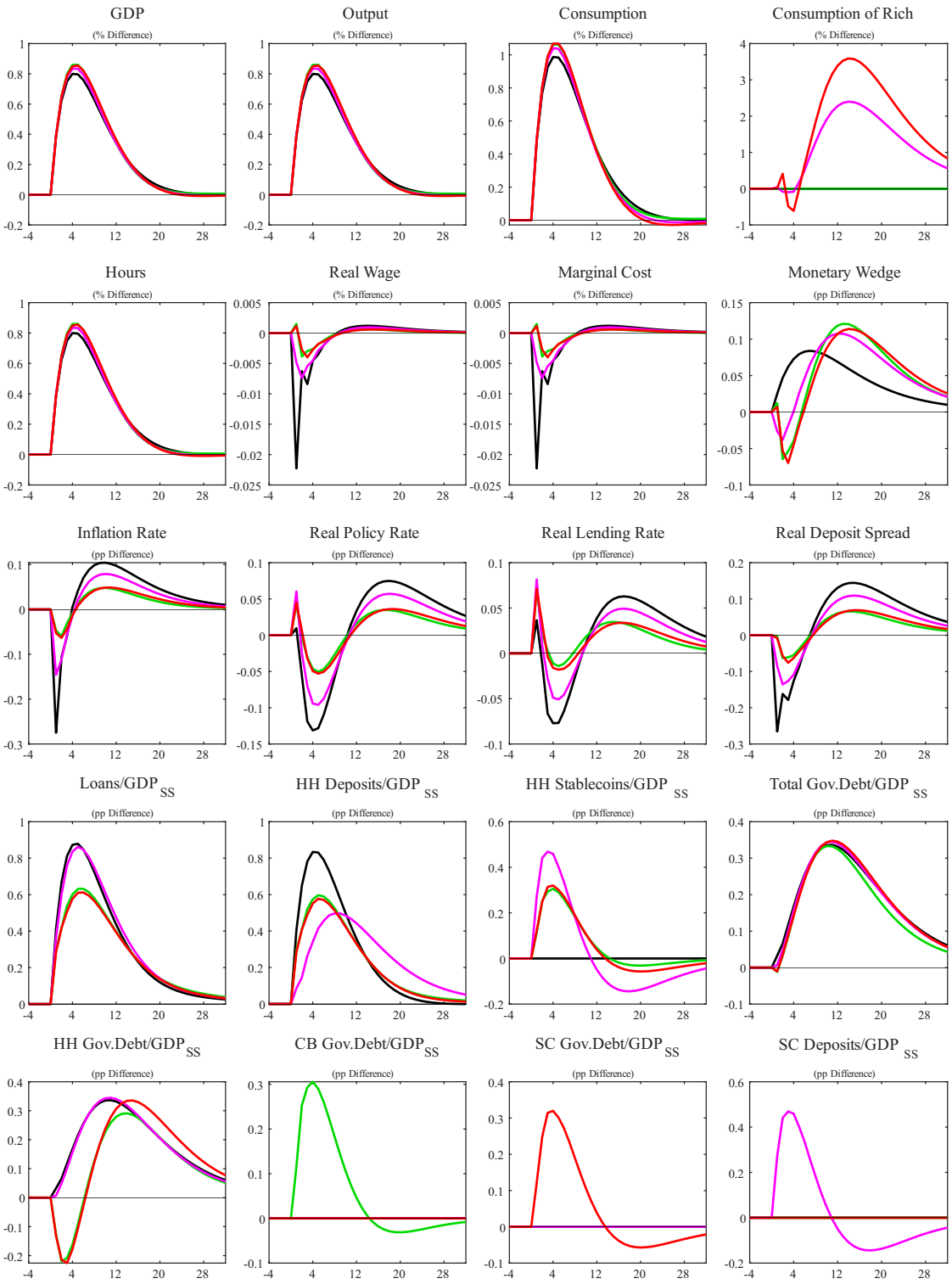


Figure 6. Consumption Demand Shock. One-standard-deviation shock at the posterior mean. Horizontal axis in quarters, shock at $t = 1$. Lines for the economy without stablecoins are in black, for CBDC-backed stablecoins in green, for deposit-backed stablecoins in pink, and for government-debt-backed stablecoins in red.

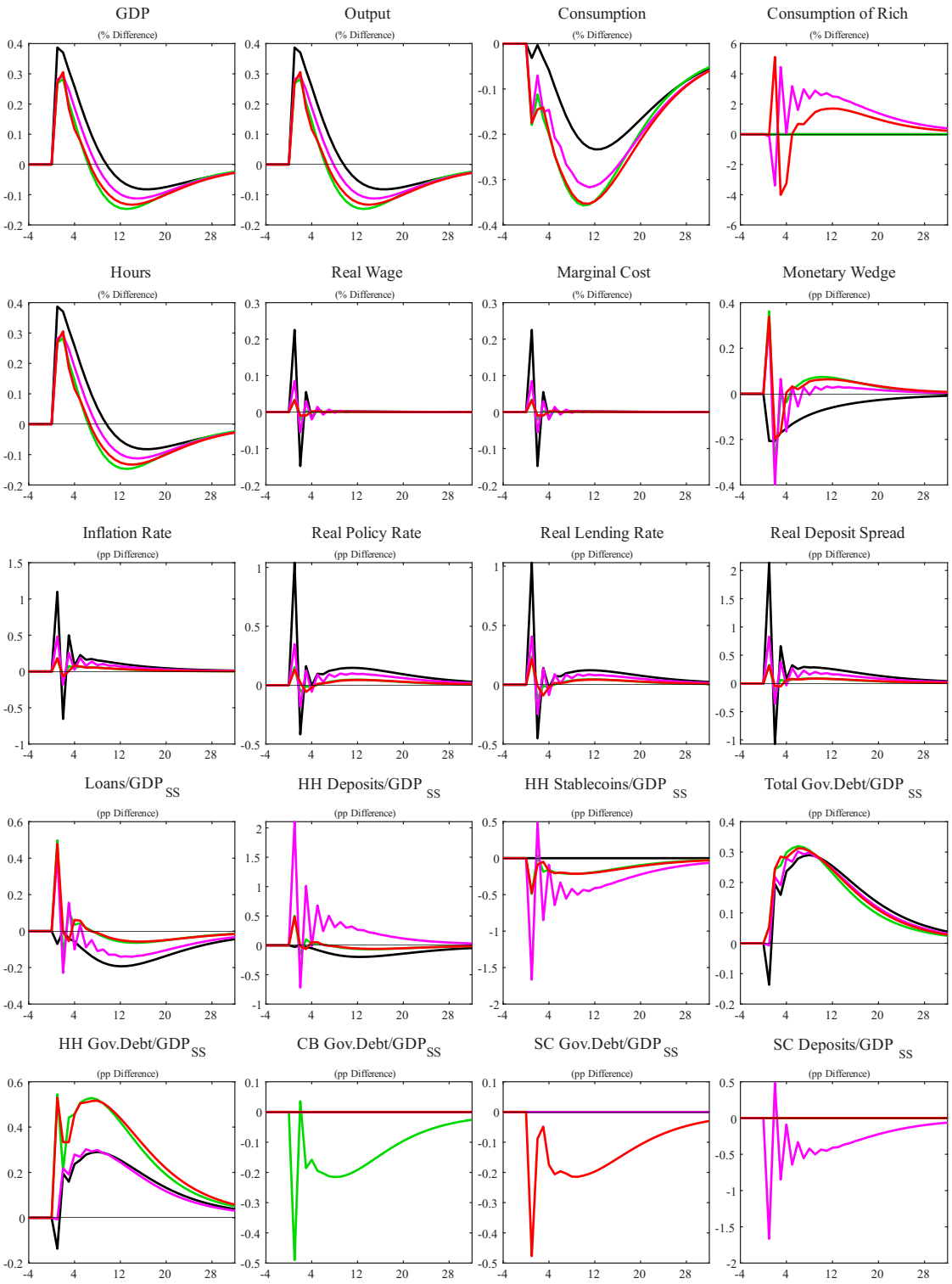


Figure 7. Government Spending Shock. One-standard-deviation shock at the posterior mean. Horizontal axis in quarters, shock at $t = 1$. Lines for the economy without stablecoins are in black, for CBDC-backed stablecoins in green, for deposit-backed stablecoins in pink, and for government-debt-backed stablecoins in red.

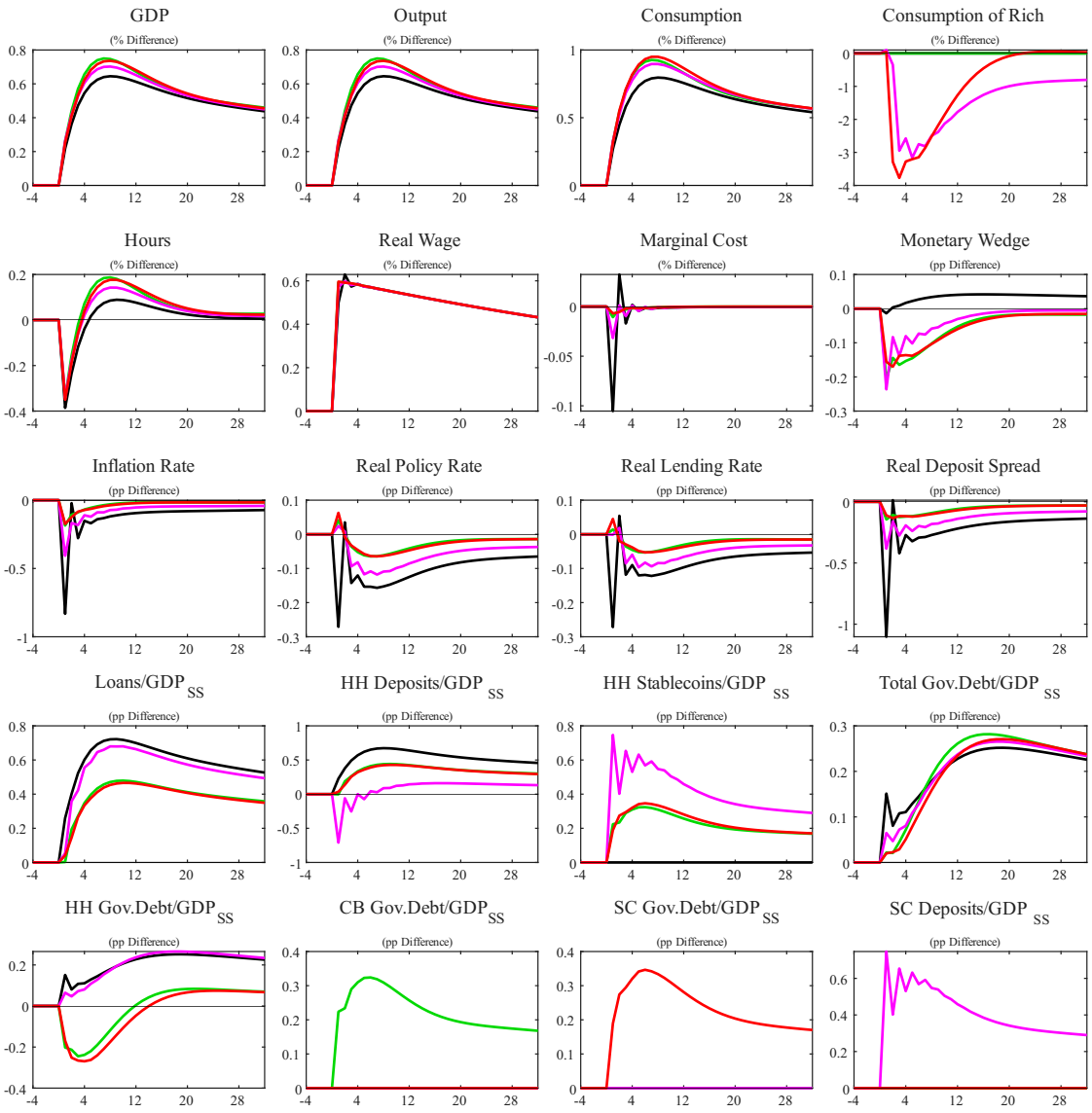


Figure 8. Technology Shock. One-standard-deviation shock at the posterior mean. Horizontal axis in quarters, shock at $t = 1$. Lines for the economy without stablecoins are in black, for CBDC-backed stablecoins in green, for deposit-backed stablecoins in pink, and for government-debt-backed stablecoins in red.

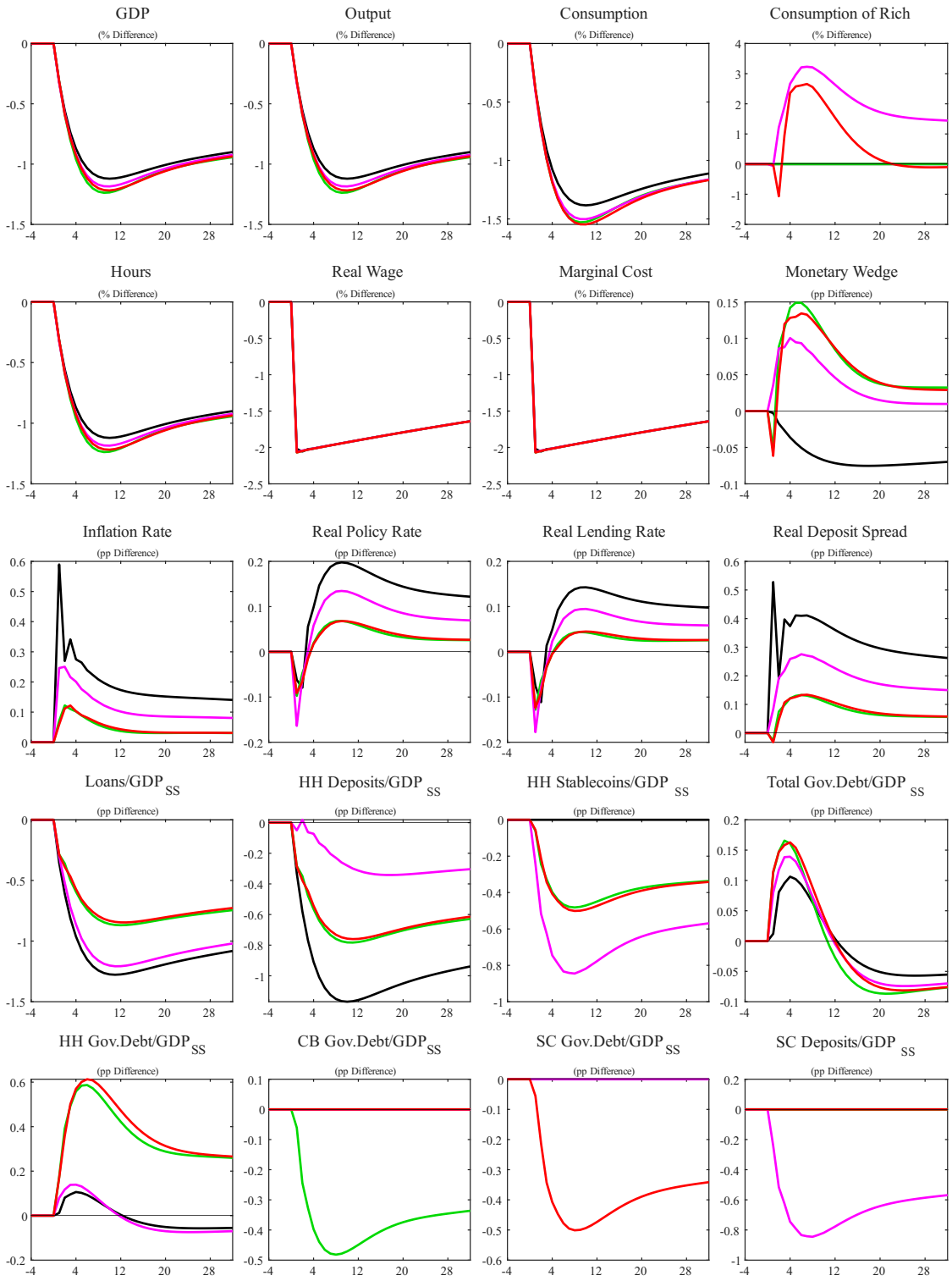


Figure 9. Markup Shock. One-standard-deviation shock at the posterior mean. Horizontal axis in quarters, shock at $t = 1$. Lines for the economy without stablecoins are in black, for CBDC-backed stablecoins in green, for deposit-backed stablecoins in pink, and for government-debt-backed stablecoins in red.

7.3. Monetary Policy Shocks

Figure (10) shows an impulse response to an expansionary monetary policy shock, specifically a decrease in S_t^{int}.

This shock has aspects of both a real and a financial shock. However, for the difference across the regimes that we study in this paper, the financial aspect is more important. Specifically, the shock increases the relative financial return of deposits relative to stablecoins and thereby triggers a substitution away from stablecoins - see the subplot "Real Deposit Spread".

Because the shock reduces the real interest rate (in the economy without stablecoins, after the impact quarter), it stimulates real activity and causes higher inflation, and increased real activity requires additional liquidity. In the economy without stablecoins this liquidity is obtained solely from banks. In the economy with stablecoins, because of the movement of the spread against stablecoins, the liquidity adjustment is costlier, with additional borrowing from banks needed to offset reduced holdings of stablecoins. As a result, liquidity and therefore real activity do not increase by as much, with output falling briefly on impact before it rises, and the real effect of the shock is dampened. This is once more most pronounced in the case of CBDC-backed and government-debt-backed stablecoins, while in the case of deposits-backed stablecoins the liquidation of stablecoin releases additional bank deposits on to the market and thereby creates easier liquidity conditions. To summarize, as for other financial shocks, in the presence of monetary policy shock the availability of stablecoins serves as a useful additional shock absorber.

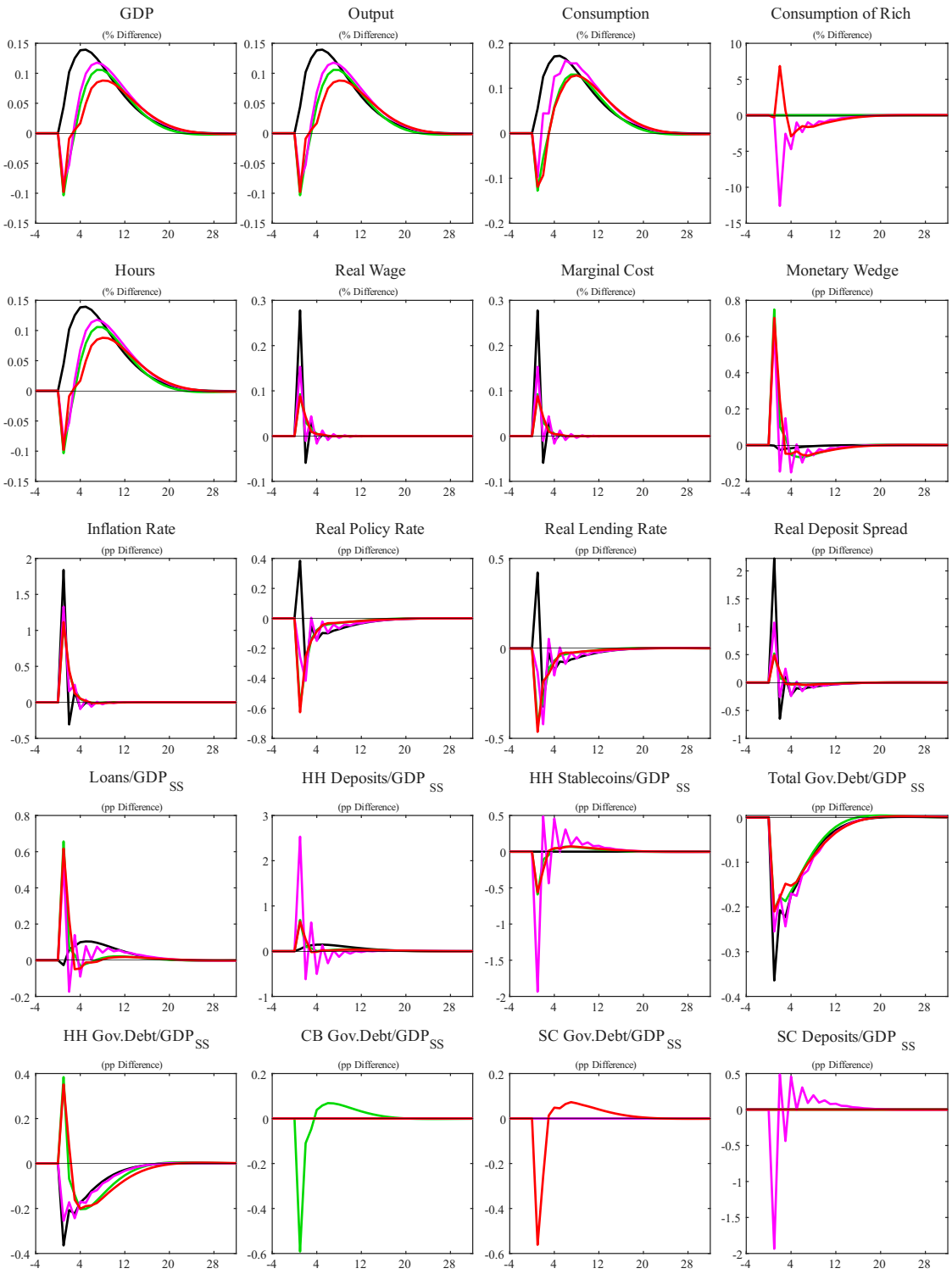


Figure 10. Monetary Policy Shock. One-standard-deviation shock at the posterior mean. Horizontal axis in quarters, shock at $t = 1$. Lines for the economy without stablecoins are in black, for CBDC-backed stablecoins in green, for deposit-backed stablecoins in pink, and for government-debt-backed stablecoins in red.

8. Conclusions

to be written

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A Robustness: Quantity-Based Stablecoin Estimates

Table 7 reports the full set of quantity-based estimates used to select the baseline stablecoin-demand process. The preferred specification scales aggregate USDT plus USDC supply by M2 and removes a linear deterministic trend before estimating the quarterly AR(1) process.

Table 7. Quantity-Based Estimates of the Stablecoin Process

Series	Transformation	Obs.	ρ	Innov. s.d.	Half-life
USDT+USDC	FD log supply	34	0.521	23.731	1.06
USDT+USDC	Log supply, linear trend	35	0.805	0.316	3.19
USDT+USDC	Log supply, quadratic trend	35	0.752	0.281	2.43
USDT+USDC	Log supply/M2, linear trend	35	0.779	0.301	2.78
USDT+USDC	Log supply/M2, quadratic trend	35	0.721	0.270	2.12

Notes: The table reports quarterly AR(1) estimates. "FD log supply" is measured as $100\Delta \log(A_t^{SC})$, so its innovation standard deviation is in percentage points. The trend-residual specifications are in log points. The baseline calibration uses the log stablecoin-supply-to-M2 residual from a linear trend.

B Robustness: Google Trends Estimates of Stablecoin Demand

As an alternative proxy for stablecoin demand, we estimate the same AR(1) process using Google Trends search intensity. We collect quarterly search interest for the terms *USDT*, *USDC*, *Tether*, and *Circle*, separately for worldwide searches and U.S. searches. Because Google Trends indices are bounded and may include zeros, we transform each index G_t as $\log(1 + G_t)$. We then estimate AR(1) processes for the first difference, the residual from a linear trend, and the residual from a quadratic trend.

The Google Trends estimates are useful as a robustness check but less suitable as the baseline calibration. Search intensity captures attention rather than quantities held, and the term *Circle* is noisy because it is not uniquely associated with the USDC issuer. The most comparable Trends estimates are those for *USDT*. For worldwide USDT searches, detrended persistence is close to the quantity-based estimate. For USDC and Tether, estimated persistence is lower. Overall, the Google Trends evidence supports a moderately persistent stablecoin-demand process and does not overturn the quantity-based baseline.

Table 8. Google Trends Estimates and Comparison with Quantity-Based Baseline

Proxy	Region	Term/series	Transformation	Obs.	ρ	Innov. s.d.
Quantity	–	USDT+USDC	Log supply/M2, linear trend	35	0.779	0.301
Quantity	–	USDT+USDC	Log supply, linear trend	35	0.805	0.316
Google	Worldwide	USDT	linear trend	37	0.806	0.314
Google	Worldwide	USDT	quadratic trend	37	0.779	0.309
Google	Worldwide	USDC	linear trend	37	0.573	0.182
Google	Worldwide	USDC	quadratic trend	37	0.527	0.180
Google	Worldwide	Tether	linear trend	37	0.612	0.123
Google	Worldwide	Tether	quadratic trend	37	0.595	0.121
Google	US	USDT	linear trend	37	0.670	0.155
Google	US	USDT	quadratic trend	37	0.668	0.155
Google	US	USDC	linear trend	37	0.692	0.122
Google	US	USDC	quadratic trend	37	0.686	0.122
Google	US	Tether	linear trend	37	0.648	0.105
Google	US	Tether	quadratic trend	37	0.444	0.096

Notes: Quantity estimates use quarterly circulating supply of USDT and USDC. Google Trends estimates use quarterly average search intensity over 2017Q2–2026Q2. The term *Circle* is omitted from the main comparison because it is not uniquely tied to USDC demand. The preferred baseline in the simulations is the quantity-based USDT+USDC/M2 specification.

C Additional Estimation Diagnostics

This appendix reports the diagnostics that are not in Table 3. On these the estimation does not meet the criterion that we apply, or the results need to be read with care. Table 9 summarizes those with a numerical criterion.

Table 9. Additional Estimation Diagnostics

Diagnostic	Criterion	Result	Source
Agreement of modes across searches	scaled distance at most 0.05	77.3	Herbst and Schorfheide (2014)
Geweke test, by chain and parameter	p at least 0.05	11 of 112 reject	Geweke (1992)
Collinearity of all parameters	below 0.99	4 of 28 exceed	Ratto and Iskrev (2011)
Shift across robustness cases	at most 2 posterior s.d.	maximum 7.8	Fernández-Villaverde and Rubio-Ramírez (2008)

Notes: The scaled distance is $\sqrt{(\theta_i - \theta^*)' H (\theta_i - \theta^*)}$ between each returned mode θ_i and the best mode θ^*, with H the Hessian. The source column gives the origin of each test or of the concern it addresses; the numerical criteria are our own.

Multiple modes: Random-walk samplers can have difficulty with multimodal DSGE posteriors (Herbst and Schorfheide, 2014), so we start the mode search from dispersed points. Five of the seven converged mode searches reach the highest mode. The other two stop at a

second local mode, 31.9 log points lower, at which the credit supply and borrower risk shocks swap their persistence, with $(\rho_{mos}, \rho_{risk})$ equal to $(0.997, 0.872)$ at the highest mode and $(0.840, 0.998)$ at the second. The second mode has a Laplace weight (Tierney and Kadane, 1986) of the order of 10^{-15}, and a chain started there stays there, so the posterior in Table 1 describes the region around the highest mode. The borrower default rate, ξ, σ_{hh} and loans to GDP differ by less than one standard error across the two modes, but the role of the two financial shocks does not. The credit supply shock accounts for 46% of inflation and 50% of the policy rate in the historical decomposition at the highest mode and for 3% and 2% at the second mode, while the borrower risk shock accounts for 5% and 5% at the highest mode and for 50% and 54% at the second.

Geweke tests: The tests of Geweke (1992) compare the means of the early and late parts of each chain. Of the 112 tests by chain and parameter, 11 reject at the 5% level, against 5.6 expected by chance, for σ_{mos}, σ_{tec}, the proxy errors on the Baa spread and on delinquency, ρ_{int}, ρ_{mos}, η, φ_π and loans to GDP. None rejects at the Bonferroni threshold of 0.00045, and the smallest p-value is 0.009.

Collinearity: The criterion in Table 3 applies to the financial parameters. Among the remaining parameters, σ_{mos} (0.998), σ_{risk} (0.993), ρ_{risk} (0.992) and σ_{int} (0.990) exceed 0.99.

Robustness: The stability of DSGE parameter estimates across samples is a known concern (Fernández-Villaverde and Rubio-Ramírez, 2008). Table 10 reports the posterior mode under alternative samples and data. These are single mode searches from the baseline mode, without chains. Only the specification without hours growth meets the criterion that the financial parameters shift by at most two posterior standard deviations. The largest shift, of 7.8 posterior standard deviations, is in σ_{hh} when the crisis quarters are included. The posterior is tight, so that in economic terms the borrower default rate ranges between 0.61% and 0.84% per quarter and the retail spread between 2.21% and 2.58%.

Table 10. Posterior Mode under Alternative Samples and Data

	Baseline	All household debt	GFC included	Sample to 2007Q4	No hours growth
γ	0.058	0.058	0.083	0.099	0.051
ξ	0.254	0.212	0.239	0.192	0.262
σ_{hh}	0.270	0.256	0.334	0.249	0.275
Default rate (% per quarter)	0.62	0.71	0.84	0.79	0.61
Loan-loss rate (% p.a.)	0.77	0.77	1.06	0.80	0.78
Retail spread (% p.a.)	2.34	2.35	2.58	2.21	2.35
Largest shift (posterior s.d.)	–	3.2	7.8	5.8	1.5

Notes: "All household debt" uses the New York Fed flow into serious delinquency including student loans. The largest shift is over γ, ξ, σ_{hh}, the borrower default threshold and loans to GDP, relative to the baseline mode.

Fit of the levels: The steady state matches the data on the retail spread (2.34% against 2.24%), the loan-loss rate (0.77% against 0.77%) and the flow into serious delinquency (0.61% against 0.58% per quarter). It does not match the wholesale spread, which equals 1.56% at the posterior mean against 0.46% in the calibration target. The delinquency rate, which averages 2.90%, is a stock and is used only in log deviations.

Model-implied volatility: In the spirit of the model checks in An and Schorfheide (2007), Table 11 compares standard deviations in the economy without stablecoins with those in the estimation sample. The model implies more volatility than the data for every series shown, with the largest gaps for inflation and the policy rate. This reflects the very persistent estimated processes, which is also why the unconditional standard deviations of inflation and the policy rate are larger still. The volatility levels in Section 6. should therefore be read as comparisons across regimes rather than as predictions of the volatility of these series.

Table 11. Model-Implied and Data Standard Deviations

Series	Data	Model, 120 quarters	Model, unconditional
Inflation	1.18	5.58	8.51
Policy rate	1.76	5.67	12.93
GDP growth	2.19	3.20	3.21
Consumption growth	1.71	3.40	3.42
Hours growth	2.25	3.46	3.46

Notes: The model column is the economy without stablecoins at the posterior mean. The data exclude the masked quarters. Inflation and the policy rate are annualized and in deviations from their means, the policy rate being the cycle of the shadow rate, and growth rates are annualized.