Supplemental Appendix

Oil Prices, Monetary Policy and Inflation Surges

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A Estimation by Matching Impulse Responses

In this section, we explain how the parameters are estimated and the confidence intervals are derived. In particular, we follow Hall et al. (2012) and Mertens and Ravn (2011) who propose an estimator based on the simulated method of moments and with inference based on the delta method. Specifically, let Λ^d be the $T \cdot N \cdot S$ vector of stacked impulse responses estimated in the data, where $T = 50$ is the forecast horizon in months, $N = 6$ the number of variables that are targeted, and $S = 2$ the number of shocks considered. Also, let $\Lambda^m(\Theta_2|\Theta_1)$ be the $T \cdot N \cdot S$ vector of stacked impulse responses obtained from model simulations, where Θ_2 is the set of parameters to be estimated conditional on the calibrated parameters Θ_1. Finally, let Σ_d^{-1}be a weighting matrix. The estimator of Θ_2 is given by:

$$\hat{\Theta}_2 = \arg\min_{\Theta_2} \left[\left(\Lambda^d - \Lambda^m(\Theta_2|\Theta_1)\right)' \Sigma_d^{-1} \left(\Lambda^d - \Lambda^m(\Theta_2|\Theta_1)\right) \right]$$

For the weighting matrix Σ_d^{-1}, we follow the standard approach to use the precision of the IRFs estimated from the VAR along the main diagonal, so that estimates with a smaller variance are assigned a larger weight in the minimization. We make an exception for the contemporaneous impact of the money shock on Fed funds and the contemporaneous impact of the oil shock on the oil price, which we assign a larger weight to ensure these own impact moments are estimated more precisely.

The standard errors of $\hat{\Theta}_2$ are computed using an estimate of the asymptotic covariance matrix derived with the delta method:

$$\Sigma_{\Theta_2} = \Lambda_{\Theta_2} \frac{\partial \Lambda^m(\Theta_2|\Theta_1)'}{\partial \Theta_2} \Sigma_d^{-1} \Sigma_S \Sigma_d^{-1} \frac{\partial \Lambda^m(\Theta_2|\Theta_1)}{\partial \Theta_2} \Lambda_{\Theta_2}$$

where

$$\Lambda_{\Theta_2} = \left[\frac{\partial \Lambda^m(\Theta_2|\Theta_1)'}{\partial \Theta_2} \Sigma_d^{-1} \frac{\partial \Lambda^m(\Theta_2|\Theta_1)}{\partial \Theta_2} \right]^{-1}$$

$$\Sigma_S = \Sigma + \Sigma_s$$

and Σ denotes the covariance matrix of the estimated SVAR-based IRFs and Σ_s is the covariance matrix of the model-based impulse responses.

B Bayesian Estimation Results

We report in Table 2 the results of the Bayesian estimation of the shocks over the sample 2010-2022.

Parameter	Prior	Prior Mean	Prior stdev	Post. Mean	10%	90%
ρ^b	beta	.6	.1	.309	.252	.365
ρ^Φ	beta	.6	.1	.529	.435	.630
σ^b	invg	.15	.15	.056	.051	.060
σ^Φ	invg	.15	.15	.151	.139	.165
σ^h	invg	.15	.15	.238	.213	.261
σ^o	invg	.15	.15	.051	.045	.058
σ^m	invg	.15	.15	.041	.036	.045

Table 2: Bayesian estimation of the parameters over the sample 2010-2022.

Prior means and standard deviations are standard as in Primiceri et al. (2006). The prior standard deviations are sufficiently large to not impose serious restrictions on the parameters. The estimates imply that both the matching shock and the discount factor shock are not very persistent, with the matching shock more persistent ($\rho^\Phi = .53$ at the posterior mean) then the discount shock ($\rho^b = .31$ at the posterior mean). The estimates of the standard deviations are sensible, with the posterior means of the standard deviation for oil $\sigma^o = .051$ and money shock $\sigma^m = .041$ that are of the same order of magnitude as those estimated for the IRFs matching exercise (which were normalized to match one standard deviation of oil prices and Fed funds respectively). The mean of the standard deviation for the high-frequency volatility shock $\sigma^h = .238$ is substantially larger than that of the oil shock. Finally, the posterior means for the matching shock $\sigma^\Phi = .151$ and discount factor shock $\sigma^b = .056$ are larger than both oil and money (because of the lower persistence), but of the same order of magnitude.

C Results with the Fed Funds Rate

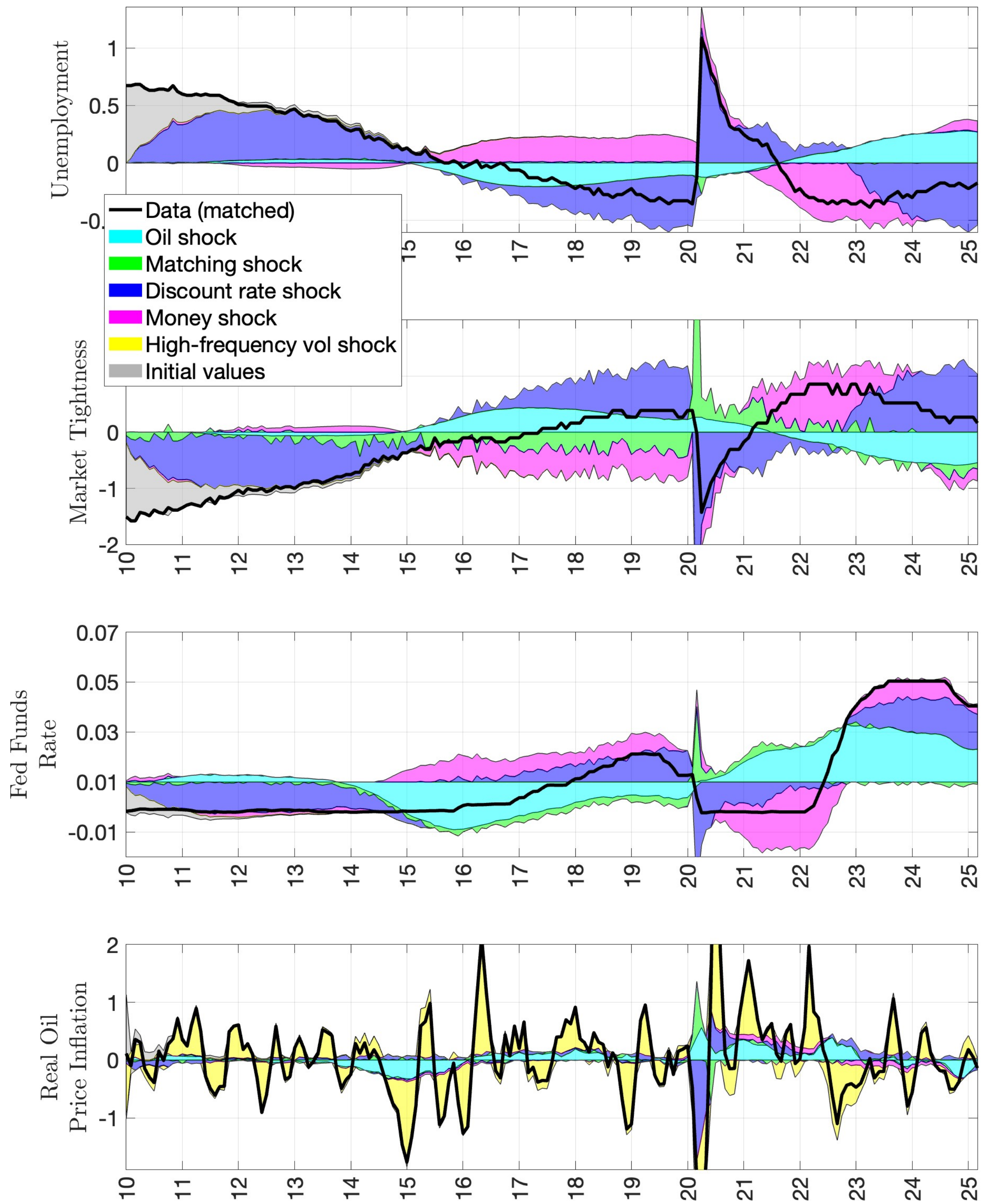

Figure 10: Historical shock decomposition of the targeted variables using the Fed Funds rate.

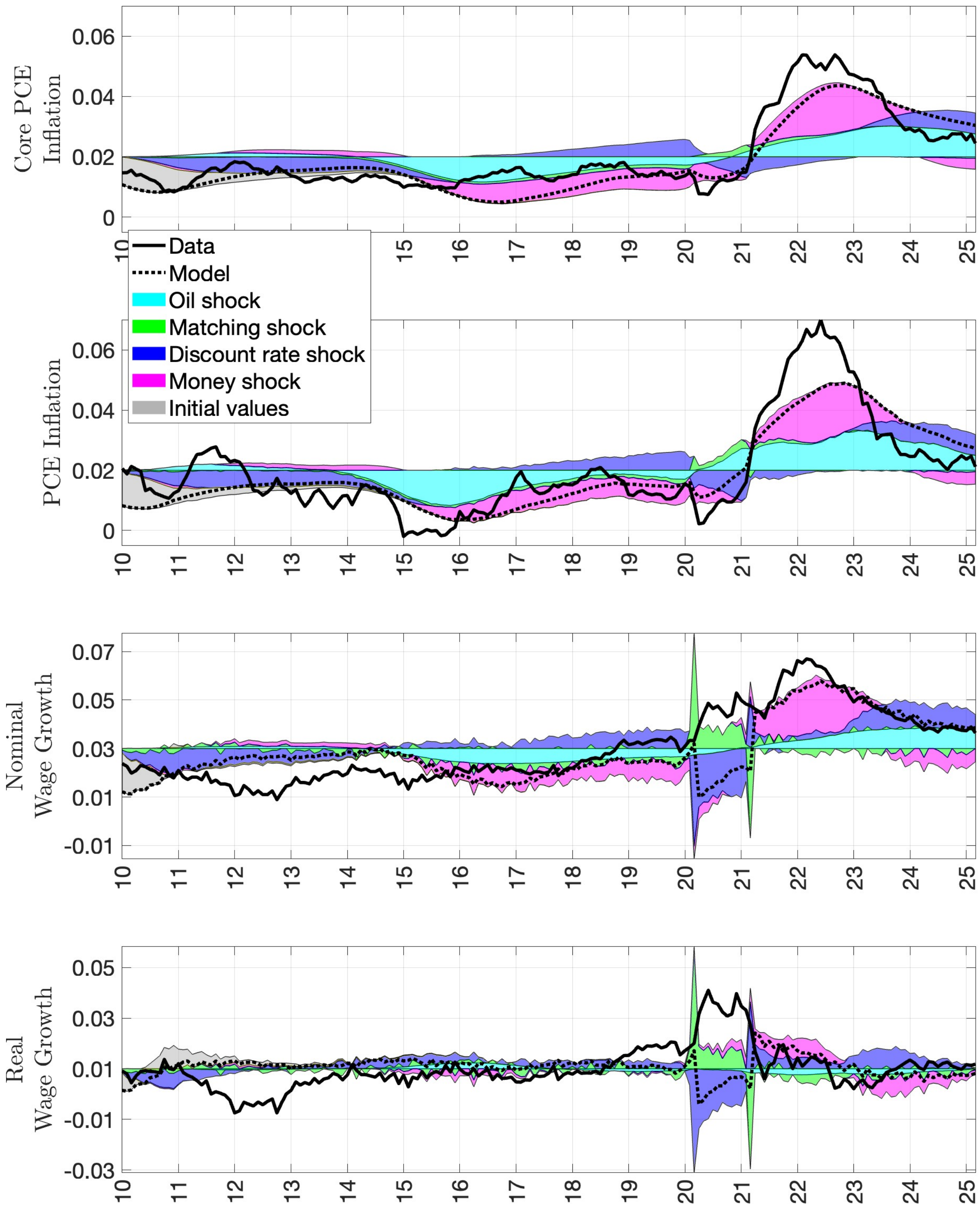

Figure 11: Historical shock decomposition of the untargeted variables using the Fed Funds rate.

D Robustness to $\phi_\pi = 1.5$ and $\phi_u = 0.5$

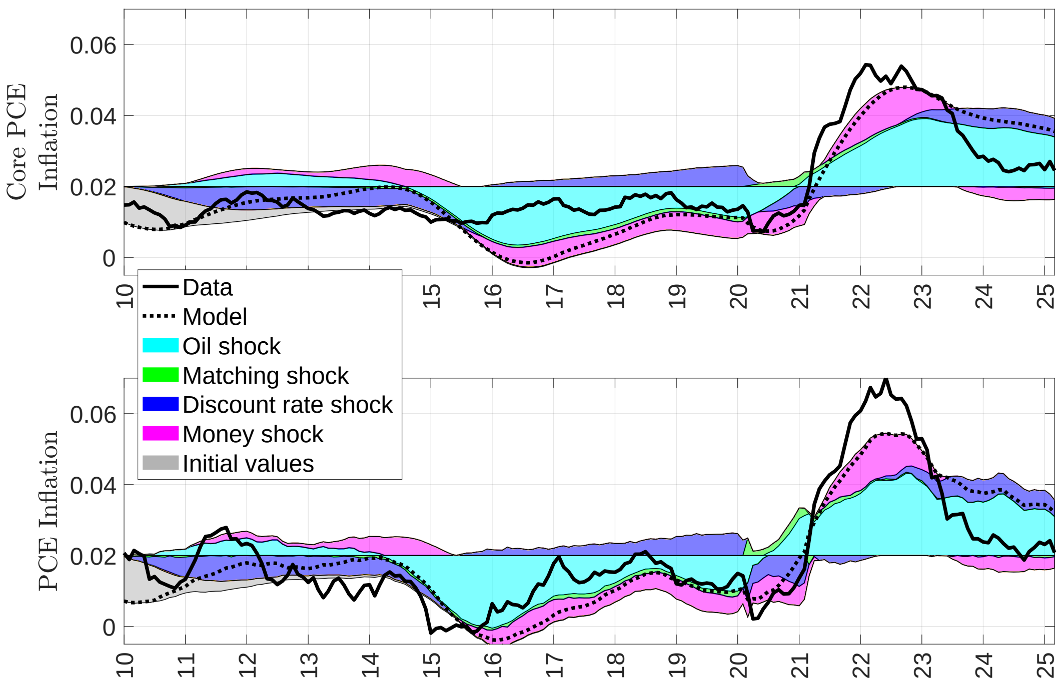

Figure 12: Historical shock decomposition of inflation with feedback coefficient on unemployment calibrated to $\phi_u = 0.5$ (annualized) and coefficient on inflation calibrated to $\phi_\pi = 1.5$.

As in our baseline (Figure 6), a combination of oil shocks and accommodative money shocks accounts for much of the inflation surge. Similarly, in both the baseline and the alternative, a combination of tight money shocks and easing of oil shocks helps explain the decline in inflation. Note also from the start of the pandemic in spring 2020 until mid 2023, the alternative generates nearly identical inflation dynamics to that in the baseline. After that, the alternative produces a slightly smaller decline in inflation relative to the baseline. Perhaps over this period, the Federal Reserve had a relatively greater focus on inflation, as our baseline suggests. In any event, the overall pattern of inflation is broadly similar across the two cases.

E Robustness to Baumeister-Hamilton Oil Shocks

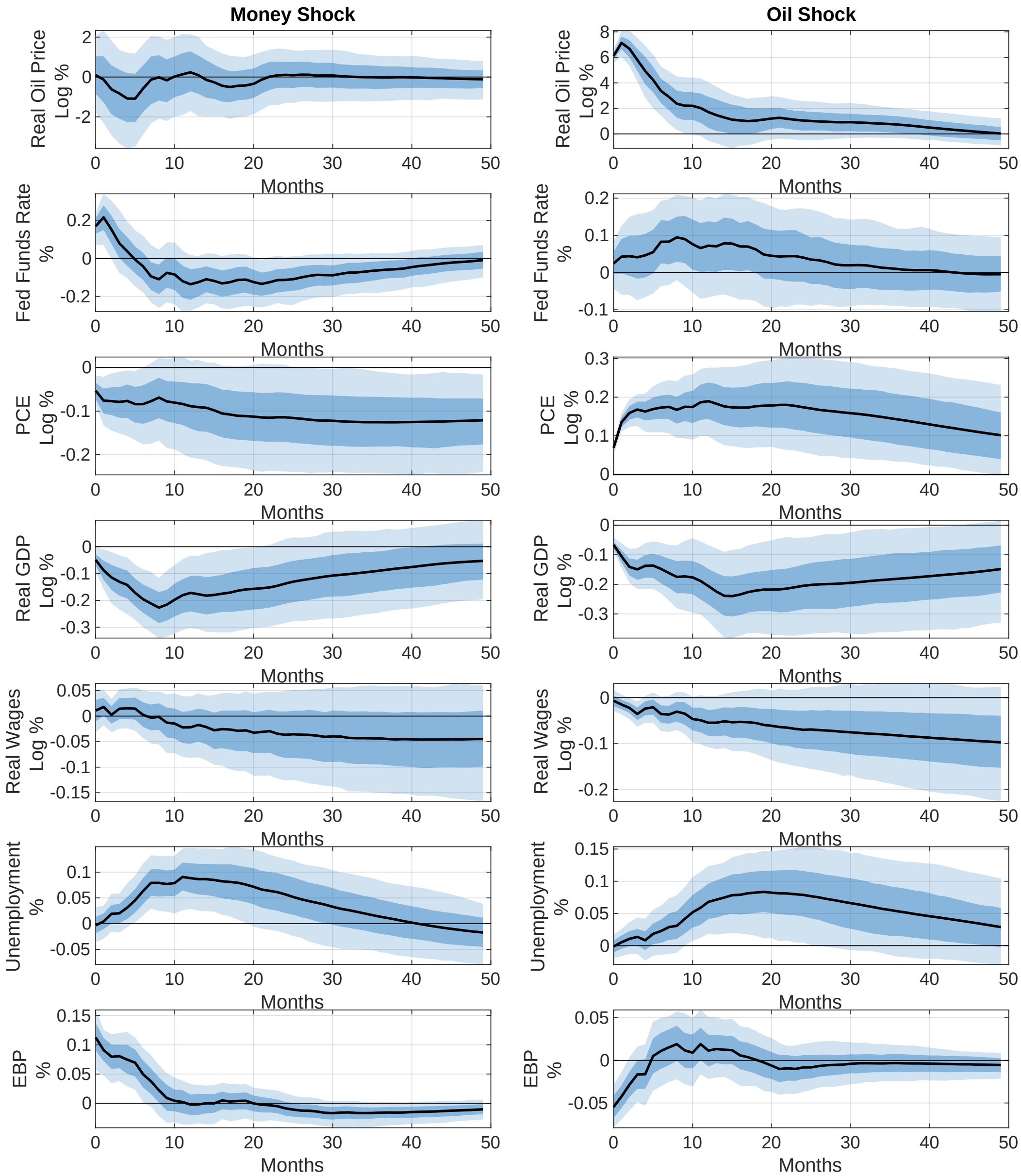

Figure 13: SVAR-based impulse responses for identified money and oil shocks, where the latter is the measure from Baumeister and Hamilton (2019). The solid line is the point estimate and the dark and light-shaded areas are 68 and 95 percent confidence bands, respectively, computed using the wild bootstrap.

References

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