ON THE STABILITY OF CALVO-STYLE PRICE-SETTING BEHAVIOR

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Abstract. An increasing literature has been concerned that the dynamics of the economy keeps switching and that, in particular, it is important to allow time variation in the degree of Calvo stickiness. We investigate this with a Markov-switching Dynamic Stochastic General Equilibrium model and show that there is little gain when allowing for such time variation. As a result we recommend to use a constant Calvo stickiness parameter, even when allowing for regime shifts elsewhere.

Date: May 11, 2015.

Key words and phrases. Markov-switching, policy-invariant, nominal rigidities, monetary policy, Bayesian method, DSGE models.

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JEL Classification: C11, C51, E31, E32, E42

We thank Francesco Bianchi, Toni Braun, Lawrence Christiano, Martin Eichenbaum, Michel Juillard, Alejandro Justiniano, Junior Maih, Giorgio Primiceri, Christopher Sims, Daniel Waggoner and Tao Zha for their very helpful suggestions; as well as participants at the 13th Annual Missouri Conference, the 9th Annual Dynare Conference (Shanghai), Macro lunch at Northwestern University, the poster session at the 2015 AEA and the seminar at the Federal Reserve Bank of Atlanta.

I. Introduction

According to the Keynesian view, monetary shocks have short-run real effects because nominal prices and wages are rigid. These rigidities imply that nominal prices and wages may take several periods to adjust to exogenous variation in monetary policy. Most of the standard medium Dynamic Stochastic General Equilibrium models [Christiano, Eichenbaum, and Evans (2005) and Smets and Wouters (2007)] employ a Calvo (1983) price-setting mechanism to model nominal rigidities. Featuring exogenous staggering of price changes across firms, the Calvo model allows a certain fraction of firms to re-optimize their prices at any given period. This fraction, represented by the Calvo pricing parameter, is constant over time, making modeling very tractable.

However, recent empirical research shows that the frequency of price changes differ between low and high inflation episodes and/or changes in monetary policy regimes. Ball, Mankiw, and Romer (1988) and Gagnon (2009) found a strong correlation between the frequency of price changes and inflation. Their results follow a simple intuition: increases in inflation-related costs lead firms to adjust prices more frequently. Fernández-Villaverde and Rubio-Ramírez (2008) and Schorfheide (2007) provide evidence that the Calvo pricing parameter is not invariant to policy changes, meaning that the Calvo models are not structural in the sense of Lucas (1976). It follows that the flexibility of prices may be a function of the current state of the economy, as modeled in state-dependent pricing models [Caplin and Spulber (1987), Dotsey, King, and Wolman (1999), Gertler and Leahy (2008), and Golosov and Lucas (2007)]. In an endogenous staggering of price changes, exogenous shifts in policy typically generate more frequent changes in prices, diminishing the short-lived real output effects and casting doubts on the real role played by monetary policy. Thus by questioning the invariance of the Calvo pricing parameter, we essentially examine the effectiveness of monetary policy as a tool for stabilizing the real economy.

Focusing on the post-World War II U.S. economy, we provide new statistical evidence on the stability of the Calvo pricing parameter. We employ a large class of DSGE models, based on a Calvo price-setting mechanism, allowing for several possible patterns of time variation in the parameters determining the degree of nominal rigidities, as well as monetary policy and disturbance variances. The regime changes are governed by first-order Markov-switching process(es). This methodology has many advantages for capturing abrupt changes in the macroeconomy. It is flexible enough to nest the setups that were previously used to find evidence of instability in the Calvo parameter and general enough to allow persistent heteroscedasticity along the line of Sims and Zha (2006). Further, the methodology provides the best way to establish whether the Calvo model is structural in the sense of Lucas (1976) by letting the Calvo pricing parameter and monetary policy coefficients switch jointly.

Using this methodology, we are able to reproduce previous results stating that the frequency of price changes is strongly correlated with inflation while the stochastic volatilities of shocks are modeled as constant over time. Firms adjust prices more often during times of higher inflation—the repricing rate dramatically increases in the high inflation period of te 1970s. This also confirms that our methodology is able to detect changes discovered with other econometric techniques. However, while taking synchronized time-varying variances in the structural disturbances into account, the instability of the Calvo parameter disappears and the model's fit is dramatically better than that of the model that only allows changes in the Calvo parameter. It becomes crucial to control heteroscedasticity while allowing for changes in structural parameters in order to avoid some significant spurious changes.

This paper also supports the idea that the Calvo pricing parameter is structural in the sense of Lucas (1976). The model that fits the data best is one that allows for independent changes in monetary policy and in the disturbance variances. The addition of time variation in the frequency of price changes with monetary policy switches does not improve the fit of the model and the repricing rate remains stable across time. The stability of that parameter is a serviceable result in the sense that central bankers can still analyze different policy scenarios using a DSGE model in any state of the economy. The best-fit model identifies the following timeline: the pre-Volcker period corresponds mainly to a weak adjustment of the nominal interest rate to inflation and output gap— called the "passive policy" regime— while a nominal interest rate response of more than one-to-one to inflation prevailed for the remaining years, labeled the "active policy" regime. In addition, the disturbance variances jump between "low-volatility" and "high-volatility" regimes across time. The latter prevailed during the 1970s as well as at the beginning of the recent financial crisis. Improved fit resulting from varying shock volatilities is consistent with findings from Sims and Zha (2006), Justiniano and Primiceri (2008), and Liu, Waggoner, and Zha (2011).

Despite finding no Bayesian evidence of time-variation in Calvo pricing when controlling for heteroscedasticity, the model exhibiting changes only in the Calvo parameter offers interesting insights on the episode of high inflation in the 1970s. Counterfactual analysis suggests that inflation dynamics differs dramatically across the two regimes. If the frequency of price changes would have been low during the Great Inflation era of the 1970s, inflation would have been largely moderated. The mechanism through which the frequency of price changes affects the inflation dynamics and the output-inflation tradeoff is the slope of the New Keynesian Phillips Curve (NKPC). This change in the slope, however, does not affect the output dynamics. In particular, the difference in the degree of nominal rigidities across regimes is not drastic enough to capture changes in the real effects of nominal shocks.

There are a few strands of literature to which this paper is related. The debate over the changes in the frequency with which prices change is large enough, both in microeconomics and macroeoconomics, that we only discuss a few selected papers. Klenow and Kryvstov (2008) provide some microeconomic evidence of the invariance of the frequency of price changes. Using U.S. micro-price data from 1988 to 2004, they found a small correlation (0.25) between the fraction of items with price changes and inflation. However, their sample does not cover the Great Inflation of the 1970s. Using Mexican micro data covering episodes of large and unstable inflation, Gagnon (2009) reports that the co-movement between inflation and the average frequency of price changes depends on the level of inflation. Specifically, a strong correlation appears to be present only when the annual rate of inflation is above 10–15 percent. Nakamura and Steinsson (2008) show that only the frequency of price increases covaries strongly with inflation. More recently, Vavra (2014) shows that the frequency of adjustment in micro data is countercyclical. Klenow and Malin (2011) deliver further discussions on the microeconomic evidence of price-setting.

At the macroeconomic level, the evidence for substantial change in the Calvo pricing parameter is also inconclusive. Fernández-Villaverde and Rubio-Ramírez (2008) estimate a medium-scale DSGE model, based on a Calvo price staggering, in which a "one-at-a-time" parameter from the private sector is allowed to change over time. Combining the perturbation method and a particle filter, they find strong evidence supporting the instability of the Calvo pricing parameter. However, this "one-at-a-time-parameter" approach raises some doubts, as stressed by Sims (2001), Schorfheide (2007), and Cogley (2007). First, it is crucial to capture the heteroscedasticy of U.S. macroeconomic disturbances in order to avoid misleading results. Second, changes in any structural parameters from the private sector may instead reflect changes in monetary policy. We address both issues and find that a complex approach dramatically changes results. Finally, Cogley and Sbordone (2005) reconcile a constant-parameter NKPC with a time-variation parameter Vector Autoregressions (VAR), concluding that the price-setting model is structurally invariant.

This paper also relates to the extensive literature on inference of macroeconomic models with time-varying parameters. Cogley and Sargent (2005) and Primiceri (2005) employ VAR models with time-varying parameters and disturbance shocks using U.S. data. These authors find variations in the behavior of private sector, monetary policy, as well as stochastic volatility. Sims and Zha (2006) develop a class of Markov-switching Bayesian VAR models and find substantial changes only in the stochastic volatility across time. More recently, Schorfheide (2005), Liu, Waggoner, and Zha (2011), Davig and Doh (2013), Bianchi (2013), and Bianchi and Ilut (2013) embed this Markov-switching framework in DSGE models. These authors find strong evidence supporting the idea that the behavior of the Federal Reserve has changed over time. Alstadheim, Bjørnland, and Maih (2013) investigate the stability of monetary policy in Norway, Sweden, the United Kingdom and Canada. Following this recent literature, we exploit the idea that agents take the possibility of regime changes into account when forming their expectations. The expectations-formation effects play a crucial role in macroeconomic dynamics. In particular, Bianchi (2013) shows that inflation would have been lowered during the Great Inflation if agents had taken into account the possibility of a more anti-inflationary Fededral Reserve Chairman.

From a technical standpoint, we use the unconventional[1] marginal likelihood computation methods of Sims, Waggoner, and Zha (2008), the bridge sampling of Meng and Wong (1996)'s, as well as the standard modified harmonic mean method of Geweke (1999) to compare the models with different specifications. Multimodal distributions are inherent in multivariate equations with Markov-switching and, taking this feature into account, these non-standard methods provide efficient approximations for the marginal data density (or marginal likelihood).

[1] "Unconventional" here means that these methods are not widely used by Bayesian macroeconomic practitioners for marginal likelihood inference.

The paper proceeds as follows: Section II presents the model. The estimation method is discussed in section III. Section IV contains descriptions of our main empirical findings. Section V reports the empirical evidence supporting the policy-invariance of the Calvo model. Conclusions are in section VI.

II. A Markov-switching rational expectations model

In this section we present the theoretical structure of our model, followed by a discussion of the strategy employed to implement the Markov-switching framework, and finally we describe the methods to solve and estimate the Markov-switching DSGE (MS-DSGE) models.

II.1. **The model.** Following Rotemberg and Woodford (1997), Boivin and Giannoni (2006) and Cogley, Primiceri, and Sargent (2010), we use a New-Keynesian model consisting of four agents: an infinite-lived representative household, a finished goods-producing firm, a continuum of intermediate goods-producing firms (each one producing a distinct perishable good at each period), and a central bank. The model is symmetric across each agent, thus allowing us to concentrate on an analysis of representative agents. Five structural shocks are identified: technology shock, shock to the household preferences, markup shock, inflation target shock, and monetary policy shock. The model also considers many features that are commonly used in the literature, such as habit formation in consumption, a price setting à la Calvo (1983), and a time-varying inflation target.

We index each household by $i \in (0,1)$. Each household maximizes their expected utility

$$\mathrm{E}_t \sum_{s=0}^{\infty} \beta^s b_{t+s} \left[\ln(C_{t+s} - hC_{t+s-1}) - \int_0^1 \frac{L_{t+s}(i)^{1+\eta}}{1+\eta} di \right] \tag{1}$$

where $\beta \in (0,1)$ is the discount factor, $\eta \geq 0$ is the inverse Frisch elasticity of labor supply, h measures the importance of habit formation, L_t denotes hours worked, C_t is a Dixit-Stiglitz aggregator of differentiated consumption goods as follows

$$C_t = \left[\int_0^1 C_t(i)^{\frac{1}{1+\theta_t}} di \right]^{1+\theta_t} \tag{2}$$

and the disturbance of the discount factor b_t follows an autoregressive process

$$\ln(b_t) = \rho_b \ln(b_{t-1}) + \varepsilon_{at} \tag{3}$$

where the distribution for ε_{bt} is

$$\text{normal}(\varepsilon_{bt}|0, \sigma_b^2) \tag{4}$$

θ_t is a markup shock following the exogenous process

$$\ln(\theta_t) = (1 - \rho_\theta)\ln\theta + \rho_\theta \ln(\theta_{t-1}) + \varepsilon_{\theta t} \tag{5}$$

where the distribution for $\varepsilon_{\theta t}$ is

$$\text{normal}(\varepsilon_{\theta t}|0, \sigma_\theta^2) \tag{6}$$

Households face the budget constraint

$$R_{t-1}B_{t-1} + \Pi_t + \int_0^1 W_t(i)L_t(i)di \geq \int_0^1 P_t(i)C_t(i)di + B_t + T_t \tag{7}$$

where B_t denotes government bonds, T_t represents lump-sum taxes and transfers, R_t is the gross nominal interest rate, W_t is the nominal wage, and Π_t denotes the profits that firms pay to the household.

A monopolistically competitive firm produces a differentiated consumption good by hiring $L_t(i)$ units of labor given the constant return to scale technology Z_t

$$Z_t L_t(i) \geq Y_t(i) \tag{8}$$

where $Y_t(i)$ is the production of good i and Z_t denotes the technology shock following a unit root process with a growth rate $z_t \equiv \ln(Z_t/Z_{t-1})$, such as

$$z_t = (1 - \rho_z)\gamma + \rho_z z_{t-1} + \varepsilon_{zt} \tag{9}$$

where the distribution for ε_{zt} is

$$\text{normal}(\varepsilon_{zt}|0, \sigma_z^2) \tag{10}$$

Following Calvo (1983), each firm sets prices according to a staggering mechanism. For each period, a fraction θ_p of firms cannot reset its price optimally and indexes them according to the rule

$$P_t(i) = \pi^{1-\gamma_p}\pi_{t-1}^{\gamma_p}P_{t-1}(i) \tag{11}$$

while the other remaining fraction of firms chooses its prices $\tilde{P}_t(i)$ by maximizing the present value of futures profits

$$\mathrm{E}_t \sum_{s=0}^{\infty} (\beta\theta_p)^s \lambda_{t+s} \left\{ \Pi^p_{t,t+s} \tilde{P}_t(i) Y_{t+s}(i) - W_{t+s}(i) L_{t+s}(i) \right\} \tag{12}$$

where $\Pi^p_{t,t+s} = \Pi^s_{\nu=1} \pi^{1-\gamma_p} \pi^{\gamma_p}_{t+\nu-1}$ for $s > 0$ otherwise 1.

Monetary authority responds to deviations in inflation and output gap according to the following rule

$$\frac{R_t}{R} = \left(\frac{R_t}{R}\right)^{\rho_R} \left[\left(\frac{\bar{\pi}_{4,t}}{(\pi^*_t)^4}\right)^{\frac{\psi_\pi}{4}} \left(\frac{Y_t}{Y^*_t}\right)^{\psi_y} \right]^{1-\rho_R} \mathrm{e}^{\varepsilon_{R,t}} \tag{13}$$

where $\bar{\pi}_{4,t}$ denotes the annual inflation, π^*_t is the time-varying inflation target, ρ_R represents the interest-rate smoothing parameter, and Y^*_t is the potential output (i.e economy with a flexible price level). The distribution for the monetary policy shock $\varepsilon_{R,t}$ is

$$\mathrm{normal}(\varepsilon_{R,t}|0, \sigma^2_{R,t}) \tag{14}$$

Following Ireland (2007), the time-varying inflation target evolves as follows

$$\log\pi^*_t = (1 - \rho_{\pi^*})\log\pi + \rho_* \log\pi^*_{t-1} + \varepsilon_{\pi^*,t} \tag{15}$$

where the distribution for $\varepsilon_{\pi^*,t}$ is

$$\mathrm{normal}(\varepsilon_{\pi^*,t}|0, \sigma^2_{*,t}) \tag{16}$$

Primiceri (2006) and Sargent, Williams, and Zha (2006) provide a formal justification of a time-varying inflation target. Because the Federal Reserve's beliefs about the economy change over time, policymakers adjust the inflation accordingly. Kozicki and Tinsley (2005), Leigh (2005), Belaygorod and Dueker (2005), and Ireland (2007) provide some empirical evidence of such an adjustment. Schorfheide (2005) and Liu, Waggoner, and Zha (2011) prefer using a Markov-switching framework to capture abrupt changes in the target.

II.2. **Solving MS-DSGE models.** We proceed in several steps to implement our regime-switching models. First, because the level of technology A_t has a unit root, consumption, real wages and output grow at constant rates. These variables are transformed to induce stationarity in the following way

$$\tilde{Y}_t = \frac{Y_t}{A_t}, \quad \tilde{C}_t = \frac{C_t}{A_t}, \quad \tilde{W}_t = \frac{W_t}{A_t} \tag{17}$$

Second, we compute the steady state of the stationary model and then we log-linearize it around its steady state. The online appendix reports the details of the log-linearization. It follows that the model can be put in a concise form as follows

$$Af_t = Bf_{t-1} + \Psi\varepsilon_t + \Pi\eta_t \tag{18}$$

where f_t is a vector of endogenous components stacking in y_t and a predetermined component consisting of lagged and exogenous variables stacking in z_t. The vector f_t is $f_t' = [y_t' \quad z_t' \quad E_t y_{t+1}']$. Finally, ε_t is a vector of exogenous shocks and η_t is vector of expectational errors. This represents the `GENSYS` form of the model [see Sims (2001)].

Third, we add an index s_t, corresponding to the regime switches, that governs the time-variation of parameters into the log-linearized model. The model becomes as follows

$$A(s_t)f_t = B(s_t)f_{t-1} + \Psi(s_t)\varepsilon_t + \Pi(s_t)\eta_t \tag{19}$$

For $1 \leq i, j \leq h$, the discrete and unobserved variable s_t is an exogenous first-order Markov process with the following transition probabilities p_{ij}

$$p_{ij} = Pr(s_t = j | s_{t-1} = i) \tag{20}$$

with $p_{ij} \geq 0$ and $\sum_{j=1}^{h} p_{ij} = 1$.

The system of equations in (19) cannot be solved using the standard solution method [Sims (2002)] because of the quasi-linearity of the model. We employ the solution algorithm based on the Mean Square Stable (MSS) concept[2] proposed in Farmer, Waggoner, and Zha (2009), Farmer, Waggoner, and Zha (2011) and Cho (2012).[3] In particular, we employ the algorithm

[2]The process f_t is Mean Square Stable (MSS) if its first and second moments converge to limits as the horizons tend to infinity:

- $\lim_{t\to\infty} \mathrm{E}_0[f_t] = \mu$,
- $\lim_{t\to\infty} \mathrm{E}_0[f_t f_t'] = \Sigma$.

[3]The second concept used in the regime-switching DSGE literature is the "boundedness stability". See Davig and Leeper (2007) and Barthelemy and Marx (2011).

solution of Farmer, Waggoner, and Zha (2011) to obtain the solution of the Markov-switching rational expectations model. See the online appendix for further details.

III. Estimation Method

This section presents the general empirical strategy employed in this paper. Our model contains nine variables. The number of variables rise to twenty-one when adding the three lagged variables $\tilde{y}_{t-1}, \tilde{\pi}_{t-1}, \tilde{\pi}_{t-2}$, and the variable characterizing the flexible economy. All these state variables are stacked into the vector f_t. The solution of the model has the form of a regime-switching vector autoregression model, as illustrated in Hamilton (1989), Sims and Zha (2006), and Sims, Waggoner, and Zha (2008). In particular, the solution can be compacted to form the transition equation following a VAR(1) process as follows

$$f_t = F(s_t) f_{t-1} + C(s_t)\epsilon_t. \tag{21}$$

We use quarterly U.S. time-series from 1954:III–2009:II on three aggregate variables: real per capita GDP (Y_t^{Data}); the quarterly GDP-deflator inflation rate (π_t^{Data}); and the (annualized) federal funds rate ($\text{FFR}_t^{\text{Data}}$).[4] A detailed description of the data is provided in the online appendix. We stack this data in the following vector of observable variables:

$$y_t = [\triangle \text{lnY}_t^{\text{Data}}, \pi_t^{\text{Data}}, \text{FFR}_t^{\text{Data}}]' \tag{22}$$

The measurement equations relate the evolution of observed time series y_t to unobserved variables f_t:

$$y_t = a + H f_t \tag{23}$$

where

$$a = [100\gamma, 100(\pi - 1), 100(\pi - 1) + R^{\text{ss}}]' \tag{24}$$

It follows from (21) and (23) that only the transition equations depend on the regime s_t. This nonlinearity prevents us from applying apply the standard Kalman filter to evaluate the likelihood of the model. Hence, we exploit the Kim and Nelson (1999) filter for constructing the likelihood. The priors are The online appendix provides this technique to evaluate the likelihood and, therefore the posterior distribution.

[4]We do not include the recent U.S. data in order to avoid the zero lower bound period.

Our strategy of estimation is described in the following paragraph. We employ a Bayesian approach to estimate the parameters of our MS-DSGE model. We start by generating one hundred draws from the prior distribution of each parameter. We then use each set of points as starting points to the `CSMINWEL` program, the optimization routine developed by Christopher A. Sims. Starting the optimization process at different values allow us to correctly cover the parameter space and avoid getting stuck in a "local" peak.

IV. Were there changes in the frequency of price adjustment?

In this section, we examine whether the frequency of price adjustments has evolved over time. To do so, we first estimate and compare various versions of the DSGE model to discriminate between them. We then select the best-fit model —if any — to answer the question. We consider the following four specifications:

(1) $\mathfrak{M}_{\text{const}}$: the parameters (structural parameters and shock variances) are time-invariant.
(2) $\mathfrak{M}_{\text{freq}}$: the Calvo pricing parameter follows a 2-states Markov process.
(3) $\mathfrak{M}_{\text{vol}}$: the variances of all structural disturbances follow the same 2-regimes Markov process.
(4) $\mathfrak{M}_{\text{freq+vol}}$: the Calvo pricing parameter and shock variances are allowed to change independently according to 2-states Markov processes.

A few items deserve discussion. First, the specification $\mathfrak{M}_{\text{freq}}$ implies only a change in the Phillips curve equation (**??**). Hence, the matrix $F(s_t)$ is a function of s_t only because of the Calvo pricing parameter, $\theta_p(s_t)$. Second, the specification $\mathfrak{M}_{\text{vol}}$ takes into account heteroskedasticity. Sims and Zha (2006) reveal that such a specification is particularly adequate to U.S. macroeconomic time series. Third, the specification $\mathfrak{M}_{\text{freq+vol}}$ implies that the model allows shock variances to vary independently of changes in the Calvo pricing parameter. Such an independence is required to avoid bias in estimates. See Sims (2001).

The Bayesian priors are reported in Table 1. The priors are mostly the same. Further details on the prior are provided in section IV.2.1. The results are based on one million draws with the random-walk Metropolis–Hastings [An and Schorfheide (2007)]. We discarded the first 100,000 draws as burn-in and keep every 500^{th} draw.

IV.1. **Model comparison.** We compute the marginal data densities (MDDs), known as a measure of fit, to discriminate between various versions of the model. We employ three different methods to compute MDDs. The first method is the standard new modified harmonic mean (MHM) method illustrated by Geweke (1999) who proposes a multivariate normal distribution as a weighting function. Such a function may produce unreasonable inference when approximating a non-Gaussian posterior density as characterized by the posterior distribution of Markov-switching models. The two other methods employed in this paper — the Sims, Waggoner, and Zha (2008) method and the bridge sampling method developed by Meng and Wong (1996) — overcome this difficulty by proposing new weighting functions. The online appendix details each method.

The log values of marginal likelihood are reported in Table 3, which allows us to draw two main conclusions. First, comparing the first and second rows, we see that allowing the Calvo parameter to change over time does not improve the fit significantly while parameter count increases. Indeed, the log values of MDD for $\mathfrak{M}_{\text{freq}}$ and $\mathfrak{M}_{\text{const}}$ are statistically indistinguishable, with a difference less than 1.0 in log terms. This suggests that the changing Calvo parameter does not add anything to the fit of the model. This agrees somehwat with the findings of Del Negro and Schorfheide (2008) that the data cannot discriminate among the low rigidities and high rigidities specifications. However, it must be noted that MDD does increase slightly and does not decrease even though unnecessary increase in the number of estimated parameters can be punished by methods employed. Thus the model with a time-varying Calvo parameter does not worsen the fit and can be used.

Second, allowing for the volatilities of the shocks to be time-varying improves the fit considerably by more than a 100 in log-terms with respect to $\mathfrak{M}_{\text{freq}}$ and $\mathfrak{M}_{\text{const}}$. This improvement corroborates with the previous findings [Sims and Zha (2006) and Liu, Waggoner, and Zha (2011)]. Hence, there are two best-fit models; $\mathfrak{M}_{\text{vol}}$ and $\mathfrak{M}_{\text{freq+vol}}$. Because their log-MDDs are extremely close, we cannot discriminate between both of them. Since the results from these two models are quite similar, we report the results from $\mathfrak{M}_{\text{freq+vol}}$ and provide some explanations for the similarities of both models.

Finally, it is apparent that all three methods for MDD computing deliver very close numerical results, which reinforces our conclusions.

IV.2. **The best-fit model, $\mathfrak{M}_{\mathbf{freq+vol}}$.** As it was mentioned earlier or above, we have incorporated two sources of time variation in the model called $\mathfrak{M}_{\text{freq+vol}}$. First, we allow the parameter that determines the degree of nominal rigidity in the economy (θ_p) to evolve as a two-state, first-order Markov-switching process. It follows that (**??**) becomes

$$\tilde{\pi}_t = \frac{\beta}{1+\gamma_p\beta}\mathrm{E}_t\tilde{\pi}_{t+1} + \frac{\gamma_p}{1+\gamma_p\beta}\tilde{\pi}_{t-1} + \frac{(1-\theta_p(s_t)\beta)(1-\theta_p(s_t))}{\theta_p(s_t)(1+\gamma_p\beta)}\tilde{w}_t + \tilde{\theta}_t \tag{25}$$

where $s_t = \{0, 1\}$ is an unobserved state variable.

Second, all shocks variances, except the inflation target shock[5], can change over time according to an independent Markov-switching process $s_t^{\text{vol}} = 1, 2$ — "low-" and "high-volatility" regimes. Liu, Waggoner and Zha (2011) have shown that it is sufficient to only allow two states to account for changes in shocks variances in a Markov-switching framework.

IV.2.1. *The prior.* Following closely Cogley, Primiceri, and Sargent (2010), we have calibrated three parameters. Due to the fact that the inverse of the Frisch elasticity of labor supply (η), steady-state price mark-up (θ), and Calvo parameter (θ_p) are not identified separately, we set the inverse of the Frisch elasticity of labor supply to two and the steady-state price mark-up to 0.10. This allows us to examine the behavior of the frequency of price adjustment in the settings of these models. We also calibrate the smoothing of the inflation target shock to 0.995. Since we estimate the model with a drifting inflation target, we set the indexation to past inflation (γ_p) to zero.

Most of the priors are rather dispersed. We report the specific distribution, the mean, and the standard deviation for each parameter. The priors are summarized in the column "Prior" of Table 1.

First, we begin with the prior distributions of preference h, β and technology parameter γ. The prior distributions for these parameters are closely following those in Cogley, Primiceri, and Sargent (2010) and Justiniano, Primiceri, and Tambalotti (2010). It may be worth noting that the discount factor has been transformed $100(\beta^{-1} - 1)$ to make the estimation easier. This prior is gamma distribution with the mean 0.25 and the standard deviation 0.10, implying a value of β equal to 0.9975 and corresponding to the value obtained in Smets and Wouters (2007) and in Altig, Christiano, Eichenbaum, and Linde (2011). The transformed

[5]We come to the same conclusion when allowing the inflation target to change with the other disturbance shocks.

steady-state technology growth-rate follows a Normal distribution, with the mean 0.50 and the standard deviation 0.10. These values imply that the mean of γ is 1.005 corresponding to an annual growth rate of 2 percent.

Second, we discuss the prior distributions for parameter determining the nominal rigidities in the model–frequency of non-adjustment in pricing $\theta_p(s_t)$. The priors for the Calvo parameter, $\theta_p(s_t)$ follows a Beta distribution. The means are set differently between the two models: in $\mathfrak{M}_{\text{freq}}$ means are symmetric and centered at 0.66 for both regimes. For $\mathfrak{M}_{\text{freq+vol}}$ we take a stand and push the change between regimes which makes our conclusion of lack of change even stronger: the mean 0.75 and the standard deviation 0.10 under Regime 1 ($s_t = 1$) and the mean 0.55 and the standard deviation 0.10 under Regime 2 ($s_t = 2$). This implies the mean of the nominal contract durations for Regime 1 and 2 are respectively equal to four and two quarters. Logically, we label the former as the "low-frequency" regime and the latter as the "high-frequency" regime. Note that we have experimented with symmetric priors and our conclusions remain unchanged.

Third, we discuss the prior distributions of shock processes in the model. For the smoothing parameters, ρ_z, ρ_p, ρ_b, and ρ_r, we impose weakly-informative beta priors centered at 0.6 with the exception of ρ_z, which is centered at 0.4 due to the unit root in labor productivity. Their standard deviations are set to 0.2. These hyperparameters are in line with those used in most studies [Justiniano and Primiceri (2008) and Smets and Wouters (2007)]. Following Liu, Waggoner, and Zha (2011), we impose the same priors for the shock variances across regimes. Specifically, monetary policy shock and price markup shock variances follow an Inverse-gamma distribution with the mean 0.15 and the standard deviation 1.00. The intertemporal preference shock and technology shock variances also follow an Inverse-gamma distribution, but with the mean 0.50 and the standard deviation 1.00. Finally, we discuss the prior duration for each regime.

The prior on the transition matrix governing the Calvo pricing parameter follow a Beta distribution with the mean 0.90 and the standard deviation 0.10, corresponding to a prior duration of twelve quarters.

When the variances of shocks are allowed to change, we impose a Beta distribution with the mean 0.90 and the standard deviation 0.10 for the transition probabilities $p_{i,i}$. This value implies a prior duration of a regime between six and seven quarters. Our prior duration on the transition matrix governing disturbance variances is reasonably based on findings in the previous literature [Sims and Zha (2006)].

IV.2.2. *The posterior.* Table 1 reports the posterior distribution for each parameter of the model $\mathfrak{M}_{\text{freq+vol}}$. Prior to focusing on the estimate for the time-varying parameters, we analyze some other key parameters.

The estimate for $100(\pi - 1)$ is 0.4723, which implies an annual inflation rate of the economy around 2 percent. The estimated steady-state technology growth rate (γ) is 0.4204, implying a growth rate of the economy of 1.68 percent per annum, which is consistent with other macroeconomic studies.

Among the monetary policy parameters, the estimate for the nominal interest rate response to inflation is 1.4938 with the tight probability interval $[1.1610; 1.9502]$. its response to an output gap is 0.5012 with relatively tight error bands $[0.3624; 0.7855]$. The estimate for the smoothing interest rate ρ_r is 0.5880, which is reasonably close to Cogley, Primiceri, and Sargent (2010) but differs from the medium-scale DSGE literature [Christiano, Eichenbaum, and Evans (2005) and Smets and Wouters (2007)].

Among the shock processes, the persistence parameters for all shocks except the preference shock (ρ_b) are small, with a persistence of markup shock equal to 0.3798 and a persistence of productivity shock equal to 0.2306. The estimate for the AR(1) coefficient for the preference shock is 0.8534 and the corresponding error bands are tight $[0.7941; 0.9076]$.

Regarding the structural disturbance variances, the model $\mathfrak{M}_{\text{freq+vol}}$ clearly captures two distinct regimes. Estimates for the standard deviations of the shocks under Regime 1, "high-volatility" regime, are larger than those under Regime 2, "low-volatility" regime. More specifically, the estimated standard deviations for the markup shock (σ_p) and the preference shock (σ_b) are about twice as high in the "high-volatility" regime. However, most change occurs in the monetary policy shock (σ_r) whitch is approximately seven times more volatile. The estimated standard deviations of the productivity shock (σ_z) decreases from 1.0179 under Regime 1 to 0.7307 under Regime 2.

Figure 1a displays the (smoothed) probabilities—evaluated at the posterior mode—of the "high-volatility" regime in the red line for the model $\mathfrak{M}_{\text{freq+vol}}$. The probability of the "high-volatility" regime starts to increase during the start of 1955, rapidly reaches its peak in 1956, and quickly decreases just prior to 1960. Whileremaining low during the next decade, the probability skyrockets to 1.0 in 1970 and through the beginning of the 1980s, covering a time in which two big oil shocks occured. One last peak is observed around 2008, corresponding to the beginning of the Great Recession. The following transition matrix

$$P^{\text{vol}} = \begin{bmatrix} 0.7652 & 0.0663 \\ 0.2348 & 0.9337 \end{bmatrix} \tag{26}$$

shows that the "low-volatility" regime is more persistent than the "high-volatility" regime. This timeframe is supported by existing literature [Davig and Doh (2013), Bianchi (2013) and Liu, Waggoner, and Zha (2011)].

We now discuss the estimates for the Calvo pricing parameter $[\theta_p(s_t)]$ across the two regimes. The estimates for $\theta_p(s_t = 1)$ is 0.8796, implying an average price duration of 4.5 quarters. The estimates for $\theta_p(s_t = 2)$ is 0.6065, which is close to the mean of its prior, suggesting that Regime 2 ("high-frequency" regime) does not occur for a long period of time, letting the prior dominate the posterior. The smoothed probabilities, reported in Figure 1b, provide evidence supporting this intuition. Regime 1 ("low-frequency" regime) dominates throughout the sample period, although there is a small probability of about 20 percent, that the "high-frequency" regime occurs between the late 1970 and the early 1980. In other words, the "high-frequency" regime never occurs. Such a result gives us the reason why we cannot discriminate between $\mathfrak{M}_{\text{freq+vol}}$ and $\mathfrak{M}_{\text{vol}}$. Indeed, both models are strictly similar[6] in the sense that they allow time-variation in all shock variances while letting completely constant the price-setting behavior over time.

IV.3. **When keeping volatility of the shocks constant.** In this section, we examine the time variation in the frequency of price adjustment while the disturbance shocks are constant across time, $\mathfrak{M}_{\text{freq}}$. Although this version of the model does not fit nearly as well as our best-fitting model, there are several reasons to examine its implications. First, this model's fit does is not worse than the constant-parameters model. Hence, this setting can still be used for economic analysis. Second, the model reflects the dominant view that firms adjust more frequently their prices in periods of high-inflation, and its economic implications allow us to better understand the role of such private-sector changes in the economy.

[6]Results from $\mathfrak{M}_{\text{vol}}$ are available upon request.

Table 1 reports the mode for each parameter with a 90 percent probability interval for both the structural parameters and shock processes of the model $\mathfrak{M}_{\text{freq}}$. The estimates for most structural parameters are quite similar to those in $\mathfrak{M}_{\text{freq+vol}}$. There are, however, some noticeable differences. First, the estimate for the Taylor-rule coefficient for inflation (ψ_π) is equal to 1.3207, which is slightly lower than the estimate of the model $\mathfrak{M}_{\text{freq+vol}}$. The second notable difference concerns the persistence of the markup and productivity shocks. The estimate for the persistence of the markup shock (ρ_p) decreases from 0.3798 in $\mathfrak{M}_{\text{freq+vol}}$ to 0.1209 in $\mathfrak{M}_{\text{freq}}$. The estimate for the persistence of the productivity shock (ρ_z) increases to 0.3974 when the size of shocks is not taken into account.

Regarding the estimate for shocks variances, the highest variance is the preference shock (σ_b) with a mean of 2.8059. The estimate for other standard deviations of shocks lie between 0.1583 and 0.6506. The 0.90 percent error bands for all the shock variances indicate that uncertainty about them is extremely small, except for the preference shock standard deviation with the probability interval $[2.1092; 3.6600]$.

It is striking to observe that price setting behavior by firms has significantly changed over time. Our estimates provide two distinct regimes of the Calvo pricing parameter $[\gamma_p(s_t)]$ with a value around 0.8720 under Regime 1—the "low-frequency" regime, and 0.7162 under Regime 2—the "high-frequency" regime. Their tight 90 percent error bands do not overlap, suggesting that the estimates are robust.

The estimate for the Calvo parameter under the "low frequency" regime, implying a price duration around 9 quarters, is consistent with the previous macroeconomic literature [Smets and Wouters (2007) and Justiniano and Primiceri (2008)], although higher than those reported in the microeconomic studies [Blis and Klenow (2004)]. However, the "high-frequency" regime corresponds to a price duration around 3 quarters and corroborates with the finding of Blis and Klenow (2004).

Figure 2 depicts 400 independent draws from the prior distribution (on the left panel) and every $2,500$th draw from the posterior distribution. The black line in each panel indicates the posterior mode. The comparison between the prior and posterior distributions allow us to assert the informative content of the data. The posterior of the Calvo parameter under Regime 1, $\theta(s_t = 1)$, is tighter relative to the prior distribution. There is also information about this parameter under Regime 2 [$\theta(s_t = 2)$] although its posterior is larger relative to the posterior under Regime 1.

Figure 3 depicts the posterior at mode as a function of $\theta(s_t = 1)$ in dotted black line, and a function of $\theta(s_t = 2)$ in red line. Once again, this Figure demonstrates how the Calvo parameter influences the posterior. Moreover, most of the draws generated from the posterior distribution concentrate in the highest probability region. We also examine the prevalence of regimes at each date. The smoothing algorithm of Kim (1994) makes an inference on s_t using all the information in the sample, as opposed to the Hamilton (1989) filtered algorithm that makes an inference on s_t using only the information at date t.

Figure 4 displays the (smoothed) probabilities of the "high-frequency" regime of price changes in red line. To highlight the connection between this regime and inflation, we display the time series of U.S. inflation in the background. The shaded grey areas denote U.S. NBER-defined recessions of the United States.

It is clearly illustrated that the probability of high frequency of price adjustments is near one during periods of high inflation and near zero for the remaining years.

According to these estimates, firms do adjust prices more often in a high-inflation environment. We interpret this result to mean that price reoptimizations become more frequent to compensate their increasing costs due to high levels of inflation. Interestingly, these findings are consistent with Ball, Mankiw, and Romer (1988), who examine the relation between inflation and the size of real effects of nominal shocks.

Further, Gagnon (2009) documents the relation between inflation and the frequency of price changes by using microeconomic data in Mexico. He comes to the same conclusion.

IV.3.1. *Economic implications.* First, we examine and compare the dynamics across the two regimes through impulse response analysis. Figure 5 shows the impulse responses to three economic disturbances. The first column depicts the responses to a markup shock under the "low-frequency" regime (in grey area) and the "high-frequency" regime (dotted red line). After a markup shock standard deviation, inflation and output follow the opposite direction while the nominal interest rate increases. The responses are remarkably similar across the two regimes.

The second column depicts responses to a preference shock under the "low-frequency" regime (in grey area) and the "high-frequency" regime (dotted black line). The patterns of each variable do not change dramatically across the regimes, except for inflation. The response of inflation is more pronounced and persistent under the "low-frequency" regime. As expected, inflation, output, and nominal interest rate increases for both regimes.

Although there are small differences across the two regimes when analyzing monetary policy shocks, the macroeconomic variables follow similar pattern under both regimes. Therefore, the real effects of monetary policy shock stays the same. The 90 percent error bands overlap, which reinforce the results. Once again, the inflation reaction is much weaker under the "low-frequency" regime, corresponding to low-inflation environments.

Overall, the transmission mechanisms appear to remain stable across the two regimes. The difference in the degree of nominal rigidities across regimes is not drastic enough to capture changes in the real effects of nominal shocks. A closer inspection is performed by looking the values of the slope of the NKPC, κ. This slope, describing the relationship between inflation and real marginal costs, is largely influenced by the parameter θ_p, which determines the degree of nominal rigidity in the economy.

A priori, the smaller the slope, the larger the nominal rigidity and the impact of monetary policy on real activity. Table 2 reports the slope across the two regimes of the model $\mathfrak{M}_{\text{freq}}$. As is clearly visible from this Table 1, the slope is very different across the two regimes of frequency of price adjustments. The estimated mode for $\kappa(s_t = 1)$, under the "low-frequency" regime, is 0.0190 with tight probability intervals $[0.0019; 0.0302]$; whereas under the "high-frequency" regime, the estimated mode for $\kappa(s_t = 2)$ is 0.1129 with probability intervals $[0.0955; 0.4621]$. The fact that the probability intervals do not overlap make results robust. However, in reference to the impulse response analysis, the drastic change in the slope of NKPC across regimes does not affect the real output impact of monetary policy shocks. What drastically changes across the regimes is the inflation dynamics. The next and final exercise confirms this finding.

The importance of variations in the frequency of price changes may be quantified through a historical counterfactual exercise assessing the impact of changing the Calvo parameter with regard to inflation dynamics: what would happen if these changes had not occurred? In order to assess the results we impose the "low-frequency" regime throughout the sample period. Figure 6 reports the actual path (black line) and the counterfactual path (red line) of inflation. It is apparent that the variability and level of inflation, during the 1970s, strongly decreases when there is a lower frequency of price changes.

Consequently, the frequency of price adjustment turns out to be an important source of fluctuations in inflation. Interestingly, our counterfactual analysis also indicates that a high frequency of price changes is associated with an upward movement in the aggregate level of prices, suggesting that inflation covaries strongly with the frequency of price increases. This corroborates with Nakamura and Steinsson (2008), who use U.S. micro level price data from 1988.

In summary, a researcher who investigates the stability of the frequency of price adjustments would not come to the same conclusion than if the model employed takes into account time variation in variance of the shocks.

IV.4. **Why does the Calvo parameter remain constant when taking heteroskedasticity into account?** An important question we ponder is why the Calvo pricing parameter remains invariant after controlling heteroscedasticity. One explanation is that the one-parameter-at-a-time approach, characterizing the model $\mathfrak{M}_{\text{freq}}$, may not be able to identify the real source of time variation.

In our setup, we calibrate the indexation parameter (ι_p) to zero in order to avoid identification issues between the indexation parameter and the Calvo pricing parameter. In consequence, the parameter that determines the frequency of price changes [$\theta_p(s_t)$] may switch regimes to compensate for mispecification in the indexation, identifying the wrong source of time-varying inflation persistence. The change in ι_p, if there is any, would be captured by the markup shock (ϵ_p) as ι_p is forced to remain unchanged over time.

A second explanation results directly from the Calvo model. An exogenous and constant staggering of price changes à la Calvo (1983) is not, a priori, incompatible with the New Keynesian theory, which predicts that an increase in the rate of inflation causes firms to adjust prices more frequently. Indeed, an adjustment of prices by firms does not necessary signify that this adjustment results from a complete re-optimization.

Adjustment and re-optimization are two different concepts. The re-optimization process implies that firms choose the price that maximizes their real profits, while the adjustment process provides no information about how producers change their prices. In consequence, the Calvo pricing parameter implies a complete re-optimization process and may not be able to capture these changes.

V. Is the Calvo pricing parameter policy invariant?

Having documented the invariance of the Calvo pricing parameter while incorporating changing volatilities, we now examine its policy invariance. DSGE models incorporate rational expectations of agents and describe agents' preferences and technology using micro-founded parameters called "deep". These parameters are thus "structural" in the sense of Lucas (1976) when the approximating model is correctly specified. This means that after a monetary policy change, the estimated preference and technology parameters remain the same. In turn, misspecified approximating DSGE models employed for policy analysis may be misleading in the sense that any policy switches would lead to a change in reduced-form parameters. The best way to evaluate the hypothesis that the Calvo pricing parameter is not structural in the sense of Lucas (1976) is to show that this parameter changes jointly with monetary policy switches. To be clear, we do not attempt to provide evidence on the empirical significance of the Lucas critique as this goes beyond the scope of our paper. We only examine whether the Calvo pricing parameter is a structural parameter; i.e, whether it remains stable across different monetary policy regimes.

We consider the following two models with time variation for parameters:

(1) $\mathfrak{M}_{\text{mp+vol}}$: The behavior of the Federal Reserve [ψ_π and ψ_y] and stochastic volatilities evolve independently over time according to two-states Markov-switching processes, respectively s_t^{mp} and s_t^{vol}.

(2) $\mathfrak{M}_{(\text{freq+mp})+\text{vol}}$: The Calvo pricing parameter [θ_p] is allowed to change simultaneously with monetary policy switches [$s_t^{\text{freq+mp}}$], while the variances of structural disturbances change independently [s_t^{vol}].

Before presenting the results, these two models deserve some comments. First, we make the transitions of the standard deviations of shocks and monetary policy coefficients independent because Davig and Doh (2013) and Bianchi (2013) have shown that doing so highly improves the fit of the model. Second, we allow only for changes in the nominal interest rate response to inflation (ψ_π) and to output gap (ψ_y) in policy changes. We impose the smoothing interest rate parameter ρ_R as constant across policy regimes. As highlighted in Bianchi (2013), this parameter is quite similar across regimes.

V.1. **Prior and posterior distributions.** Table 4 reports prior and posterior medians with a 90 percent probability interval for the structural parameters and shock processes of the models $\mathfrak{M}_{\text{mp+vol}}$ and $\mathfrak{M}_{\text{(freq+mp)+vol}}$. The priors for constant parameters are similar to those reported in the previous section, as well as the standard deviations of the shocks. We now discuss the prior distributions of the monetary policy rule. We impose an asymmetric prior for the interest rate response to inflation across the two regimes. In particular, the prior for the second regime $[s_t^1 = 2]$ corresponds to a more aggressive response to inflation—with a Normal distribution, the mean is 2.50 and the standard deviation is 0.20—than for the first regime with a Gamma distribution, the mean at 1.00 and the standard deviation at 0.20. The prior for the reaction to an output gap is symmetric across regimes. It follows a Gamma distribution with the mean at 0.30 and the standard deviation at 0.10. Finally, the interest rate smoothing parameter ρ_r follows the Beta distribution with 0.60 as the mean and 0.20 as the standard deviation. Finally, the prior mean probabilities for the process s_t^{mp} are equal to 0.95 and are associated with tight standard deviations, implying that the regimes are very persistent. Therefore, we label the Regime 1 as the "passive policy" regime and the Regime 2 as the "active policy" regime.

The estimates for structural parameters, other than monetary policy coefficients, for the $\mathfrak{M}_{\text{mp+vol}}$ and $\mathfrak{M}_{\text{(freq+mp)+vol}}$ models are close to those previously outlined. For this reason, we focus our attention on the monetary policy parameters. For $\mathfrak{M}_{\text{mp+vol}}$, the estimate for the interest rate response to inflation under the "passive policy" regime, $\psi_\pi(s_t^1 = 2)$, is 0.8237 with the error bands [0.6412; 1.1755], covering the mode of a similar parameter $\psi_\pi(s_t^1 = 2) = 0.8350$ in $\mathfrak{M}_{\text{(freq+mp)+vol}}$. This parameter is permitted to go below 1—leading to the indeterminacy region in a constant parameters model, but not necessary in a Markov-switching rational expectations model. The estimated posterior mode accepts the idea that the Federal Reserve has raised the nominal interest-rate less than one-for-one in response to higher inflation since post-World War II. In the "active policy" regime, both models imply that the estimate for $\psi_\pi(s_t^1 = 2)$ is about 2.45. The probability intervals of these parameters are very similar and clearly cover the estimates from the previous studies in DSGE literature [Christiano, Eichenbaum, and Evans (2005) and Smets and Wouters (2007)]. Overall, our estimate for these coefficients [$\psi_\pi(s_t)$ for $s_t = \{1, 2\}$] lay within a 90 percent posterior probabilities interval found by Bianchi (2013). The estimate for the interest rate response to the output gap has changed slightly between the two regimes with $\psi_x(s_t^1 = 1) = 0.5089$ and $\psi_x(s_t^1 = 2) = 0.3685$ for $\mathfrak{M}_{\text{mp+vol}}$, and $\psi_x(s_t^1 = 1) = 0.5108$ and $\psi_x(s_t^1 = 2) = 0.3777$ for $\mathfrak{M}_{(\text{freq+mp})+\text{vol}}$. Although not imposed by the prior, monetary policy responds differently to the output gap across regimes with a more aggressive response in the "active policy" regime. Finally, the mode of the estimated smoothed interest rate parameter is $\psi_{\rho_R} = 0.5804$, with a tight probability interval $[0.5253; 0.7289]$. Overall, the estimates for coefficients of the monetary policy equation are roughly the same in both models.

Regarding the parameter determining the degree of nominal price rigidities in $\mathfrak{M}_{(\text{freq+mp})+\text{vol}}$, the estimate for $\xi_p(s_t^1 = 1)$ is about 0.7542 for the "passive policy" regime and $\xi_p(s_t^1 = 2) = 0.7719$ for the "active policy" regime. As the difference in this parameter across regimes is very small, a conclusion cannot be reached that the "passive policy" regime is associated with a low frequency of nonadjustment of prices, whereas the "active policy" regime characterized by a high frequency of non-adjustment of prices. Furthermore, the 90 percent posterior probability intervals overlap, we fail to make a distinction between the estimates for two regimes. Thus, this parameter is essentially the same regardless of time period or policy. So it is not surprising to observe that the mode of this estimated parameter in $\mathfrak{M}_{\text{mp+vol}}$ lies within the probability intervals of those estimated in $\mathfrak{M}_{(\text{freq+mp})+\text{vol}}$, with a value equal to 0.7685. It then follows that in the aggregate level in U.S. economy, the average duration of prices is about 4 quarters which is consistent with the microeconomic literature [Blis and Klenow (2004)].

Figures 7a and 7b show the (smoothed) probabilities of both Markov-switching processes, s_t^{mp} and s_t^{vol}, over time for the model $s_t^{\text{mp+vol}}$. We do not report the smoothed probabilities in the $s_t^{(\text{mp+freq})+\text{vol}}$ model because the graph is nearly the same as that for the model $s_t^{\text{mp+vol}}$. The top panel depicts the smoothed probabilities (at the posterior mode of the parameters) of being in the "active policy" regime at any date. This panel also displays the evolution of the federal funds rate. It is apparent that the behavior of the Federal Reserve can be divided into a pre- versus post-Volcker era. Indeed, the probability of the "active policy" regime starts to increase slightly after Paul Volcker assumed chairmanship of the Federal Reserve, and rapidly reaches 1.0 and stays near this value until the end of the sample. This finding is consistent with Bianchi (2013) that the appointment of Paul Volcker in the mid 1970s is interpreted as a dramatic shock rather than a deliberate change in the conduct of monetary policy. Moreover, the long period of sustained "passive policy" is consistent with the widely thought that the predecessors of Paul Volcker, in particular Arthur F. Burns and G. William Miller, were not deliberately committed to a fight high-inflation [Meltzer (2009)]. Finally, estimated probabilities provide empirical evidence that it is judicious to divide the post-World War II American economy into pre- versus post-Volcker eras [see among others, Lubik and Schorfheide (2004) and Clarida, Gali, and Gertler (2000)].

The estimated probabilities of the transition matrix governing the monetary policy changes, s_t^{mp}, and the shocks variance, s_t^{vol}, are as follows

$$P^{\text{mp}} = \begin{bmatrix} 0.9914 & 0.0029 \\ 0.0086 & 0.9971 \end{bmatrix} \qquad \text{and} \qquad P^{\text{vol}} = \begin{bmatrix} 0.7652 & 0.0663 \\ 0.2348 & 0.9337 \end{bmatrix} \tag{27}$$

The estimated probabilities in the transition matrix P^{mp} are quite similar and very high, implying a highly persistent duration for each regime. The skewed 0.90 probability intervals, reported in the Table 4, reinforce the idea that both regimes are very sustainable. The estimated transition matrix P^{vol} is very similar to the one in the s_t^{vol} with a larger persistence of the "low-volatility" regime.

V.2. **Assessing fit.** The final two rows of Table 3 report the log-values of MDD for $\mathfrak{M}_{\text{mp+vol}}$ and $\mathfrak{M}_{(\text{freq+mp})+\text{vol}}$. When comparing the model with independent changes in monetary policy behavior and shocks variances, [$\mathfrak{M}_{\text{mp+vol}}$] with $\mathfrak{M}_{\text{vol}}$ allowing only drifts in variance shocks, the former delivers the best-fit with a log-value difference of 3.0 for the Bridge method and 2.0 for the other two methods, implying important changes in the behavior of the Federal Reserve over time.

Furthermore, the addition of time variation in the frequency of price changes in conjunction with monetary policy switches, $\mathfrak{M}_{(\text{freq+mp})+\text{vol}}$, does not improve the fit. This may be explained simply by the fact that the estimates for $\theta_p(s_t)$ are clearly the same across the two regimes, and in consequence, the data cannot favor one model over another.

Once again, the three marginal likelihood computation methods draw the same conclusion, reinforcing our previous results. We conclude that the Calvo model is a well-specified approximating model, guaranteeing the invariance of the Calvo pricing parameter while suggesting that it is not particularly harmful to model a Calvo parameter as time-varying if one is interested in examining economic implications possibly arising from this variation.

VI. Conclusion

We have examined the structural nature of the Calvo (1983) parameter, which determines the frequency of price adjustment, in a class of Markov-switching medium-scale DSGE models that fit the U.S. macroeconomic data from 1954 to 2009. In this setup, we allow agents to adjust their expectations based on the belief that certain features of the economy and policy are stochastic and nonpermanent.

We have solved and estimated the models under these conditions and were able to address a widely discussed question on which features of modeling aggregate prices can be considered structural. Previous research has found that the Calvo parameter is unstable and varies across high and low inflation episodes and/or a monetary policy regime. We reproduce this evidence and show that such instability largely disappears when one models heteroscedasticity in a Markov-switching Dynamic Stochastic General Equilibrium model. Our second main empirical finding indicates that the Calvo parameter is also invariant to changes in the monetary policy regime.

Although statistically dominated, the model that allows the frequency of price changes to vary across two regimes, offers interesting insights about the price-setting behavior of firms over time. When the economy is pushed into a high inflation environment, firms change their behavior and reoptimize their prices more frequently. Our results suggest that if this regime change in the firms' behavior would not have occured, then U.S. inflation would not have reached exceptional levels in the 1970s; thus implying that time variations in private sector behavior as a source of macroeconomic fluctuations played an important role.

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VII. TABLES

	Prior			Posterior								
				$\mathfrak{M}_{\text{freq}}$			$\mathfrak{M}_{\text{freq+vol}}$			$\mathfrak{M}_{\text{vol}}$		
description	density	mean	std	mode	5 %	95 %	mode	5 %	95 %	mode	5 %	95 %
$100(\beta^{-1}-1)$	N	0.25	0.10	0.1759	0.0874	0.3000	0.1506	0.0769	0.2714	0.1473	0.0790	0.2696
$100(\pi-1)$	N	0.50	0.10	0.5037	0.3256	0.6413	0.4723	0.3267	0.6457	0.4801	0.3357	0.6603
$100log(\gamma)$	G	0.42	0.03	0.4174	0.3765	0.4537	0.4204	0.3834	0.4610	0.4201	0.3820	0.4580
h	B	0.50	0.10	0.3970	0.2784	0.5120	0.4449	0.3681	0.5434	0.4483	0.3692	0.5400
θ_p	B	0.66	0.10	-	-	-	-	-	-	0.8017	0.7304	0.8766
$\theta_p(s_t^{\text{freq}}=1)$	B	0.66	0.10	0.8720	0.8410	0.9585	-	-	-	-	-	-
$\theta_p(s_t^{\text{freq}}=2)$	B	0.66	0.10	0.7162	0.5132	0.7360	-	-	-	-	-	-
$\theta_p(s_t^{\text{vol}}=1)$	B	0.75	0.10	-	-	-	0.8796	0.7795	0.9444	-	-	-
$\theta_p(s_t^{\text{vol}}=2)$	B	0.55	0.10	-	-	-	0.6065	0.4482	0.7486	-	-	-
ψ_π	N	1.70	0.30	1.2546	1.0387	1.8039	1.4938	1.1610	1.9502	1.4742	1.1593	1.9537
ψ_y	G	0.30	0.20	0.4891	0.3612	0.9054	0.5012	0.3624	0.7855	0.4934	0.3859	0.8177
ρ_b	B	0.60	0.20	0.8576	0.7806	0.9182	0.8534	0.7941	0.9076	0.8556	0.8029	0.9156
ρ_r	B	0.60	0.20	0.5087	0.2758	0.6836	0.5880	0.5077	0.7256	0.5817	0.5074	0.7298
ρ_p	B	0.60	0.20	0.1209	0.0396	0.2974	0.3798	0.1799	0.5411	0.4131	0.1987	0.5558
ρ_z	B	0.40	0.20	0.3974	0.1052	0.5895	0.2306	0.1077	0.3962	0.2301	0.1095	0.3973
$\sigma_p(st=1)$	I-G	0.15	1.00	0.1917	0.1590	0.2170	0.1078	0.0819	0.1407	0.2401	0.1828	0.3451
$\sigma_p(st=2)$	I-G	0.15	1.00	-	-	-	0.2464	0.1891	0.3445	0.1031	0.0783	0.1372
$\sigma_b(st=1)$	I-G	1.00	1.00	2.8059	2.1092	3.6600	1.9472	1.5329	2.6639	4.6598	3.4406	6.6821
$\sigma_b(st=2)$	I-G	1.00	1.00	-	-	-	4.5599	3.2067	6.4847	1.9502	1.5319	2.6738
$\sigma_z(st=1)$	I-G	1.00	1.00	0.6441	0.4929	0.9804	0.7307	0.5734	0.8799	1.0090	0.7439	1.3916
$\sigma_z(st=2)$	I-G	1.00	1.00	-	-	-	1.0179	0.7585	1.4254	0.7454	0.5846	0.8943
$\sigma_r(st=1)$	I-G	0.15	0.10	0.1588	0.1037	0.1895	0.0407	0.0333	0.0534	0.2751	0.2382	0.3564
$\sigma_r(st=2)$	I-G	0.15	0.10	-	-	-	0.2787	0.2362	0.3530	0.0411	0.0326	0.0525
$\sigma_{\pi,t}$	U	0.07	0.04	0.0868	0.0606	0.1755	0.0662	0.0353	0.1047	0.0544	0.0353	0.1006
$p_{1,1}^{\text{freq}}$	B	0.90	0.10	0.9985	0.9881	0.9997	0.9959	0.9318	1.0000	-	-	-
$p_{2,2}^{\text{freq}}$	B	0.90	0.10	0.9949	0.8629	0.9994	0.9631	0.6993	0.9997	-	-	-
$p_{1,1}^{\text{vol}}$	B	0.90	0.10	-	-	-	0.9677	0.9273	0.9851	0.9394	0.8312	0.9787
$p_{2,2}^{\text{vol}}$	B	0.90	0.10	-	-	-	0.9365	0.8267	0.9785	0.9681	0.9301	0.9876

TABLE 1. Prior and posterior of the models $\mathfrak{M}_{\text{freq}}$, $\mathfrak{M}_{\text{freq+vol}}$ and $\mathfrak{M}_{\text{vol}}$. N stands for Normal, B Beta, G for Gamma, I-G for Inverted-Gamma and U for Uniform distributions. The 5 percent and 95 percent demarcate the bounds of the 90 percent probability interval.

		posterior		
model	specifications	mode	5%	95%
$\mathfrak{M}_{\text{freq}}$	$\kappa(s_t^{\text{freq}} = 1)$	0.0190	0.0019	0.0302
	$\kappa(s_t^{\text{freq}} = 2)$	0.1129	0.0955	0.4621

Table 2. The slope of the New Keynesian Philips Curve. The 5 percent and 95 percent demarcate the bounds of the 90 percent probability interval. The parameter $\kappa(s_t) = \frac{(1-\theta_p(s_t)\beta)(1-\theta_p(s_t))}{\theta_p(s_t)(1+\gamma_p\beta)}$ is widely interpreted as the slope of the New Keynesian Phillips curve.

	specifications			marginal data densities		
model	Pricing	Policy	Shocks	MHM	Bridge	SWZ
$\mathfrak{M}_{\text{const}}$	X	X	X	-923.24	-923.20	-923.58
$\mathfrak{M}_{\text{freq}}$	s_t^{freq}	X	X	-921.29	-920.48	-920.22
$\mathfrak{M}_{\text{freq+vol}}$	s_t^{freq}	X	s_t^{vol}	-815.31	-814.41	-814.08
$\mathfrak{M}_{\text{vol}}$	X	X	s_t^{vol}	-815.51	-815.27	-815.40
$\mathfrak{M}_{\text{mp+vol}}$	X	s_t^{mp}	s_t^{vol}	-813.68	-812.61	-813.80
$\mathfrak{M}_{\text{(mp+freq)+vol}}$	s_t^{mp}	s_t^{mp}	s_t^{vol}	-815.50	-814.39	-814.36

Table 3. This Table reports the marginal data densities of each model using three different methods: (1) MHM: Modified Harmonic Mean [Geweke (1999)]; (2) The Bridge sampling [Meng and Wong (1996)]; and (3) The Sims, Waggoner, and Zha (2008) method. The index s_t^h indicates whether the "pricing" parameter (θ_p), the "Policy" parameters (ψ_π and ψ_π) or the "shocks" variances (σ) follow a two-states Markov-switching process h. The Xs indicate the parameters that remain constant over time.

	Prior			Posterior					
				$\mathfrak{M}_{\text{mp+vol}}$			$\mathfrak{M}_{\text{(freq+mp)+vol}}$		
description	density	mean	std	mode	5 %	95 %	mode	5 %	95 %
$100(\beta^{-1}-1)$	N	0.25	0.10	0.1382	0.0742	0.2529	0.1400	0.0710	0.2570
$100(\pi-1)$	N	0.50	0.10	0.4521	0.3537	0.6605	0.4525	0.3369	0.6562
$100\log(\gamma)$	G	0.42	0.10	0.4208	0.3349	0.5172	0.4193	0.3397	0.5137
h	B	0.50	0.10	0.4397	0.3888	0.5716	0.4385	0.3753	0.5518
$\theta_p(s_t^{\text{mp}}=1)$	B	0.66	0.10	0.7685	0.7442	0.8864	0.7719	0.7398	0.8907
$\theta_p(s_t^{\text{mp}}=2)$	B	0.66	0.10	-	-	-	0.7542	0.6861	0.8354
$\psi_\pi(s_t^{\text{mp}}=1)$	N	2.50	0.20	2.4514	2.0907	2.7481	2.4515	2.1275	2.7615
$\psi_\pi(s_t^{\text{mp}}=2)$	N	1.00	0.10	0.8237	0.6412	1.1755	0.8350	0.6715	1.1967
$\psi_y(s_t^{\text{mp}}=1)$	G	0.40	0.10	0.5089	0.4192	0.7422	0.5108	0.3635	0.7245
$\psi_y(s_t^{\text{mp}}=2)$	G	0.40	0.10	0.3685	0.1878	0.4386	0.3777	0.2275	0.5317
ρ_r	B	0.60	0.20	0.5804	0.5253	0.7289	0.5813	0.5147	0.7013
ρ_b	B	0.60	0.20	0.8568	0.7951	0.9097	0.8552	0.7988	0.9101
ρ_p	B	0.60	0.20	0.3174	0.1972	0.5662	0.3197	0.1728	0.5251
ρ_z	B	0.40	0.20	0.2612	0.1058	0.4959	0.2610	0.1065	0.4603
$\sigma_p(s_t^{\text{vol}}=1)$	I-G	0.15	1.00	0.2600	0.1877	0.3494	0.2608	0.1974	0.3572
$\sigma_p(s_t^{\text{vol}}=2)$	I-G	0.15	1.00	0.1156	0.0797	0.1410	0.1155	0.0864	0.1458
$\sigma_b(s_t^{\text{vol}}=1)$	I-G	1.00	1.00	4.3733	3.4189	6.6622	4.3391	3.5572	6.3813
$\sigma_b(s_t^{\text{vol}}=2)$	I-G	1.00	1.00	1.9530	1.7170	2.9398	1.9324	1.6213	2.6956
$\sigma_z(s_t^{\text{vol}}=1)$	I-G	1.00	1.00	0.9394	0.6585	1.4210	0.9393	0.6940	1.3763
$\sigma_z(s_t^{\text{vol}}=2)$	I-G	1.00	1.00	0.6747	0.3932	0.8263	0.6791	0.4927	0.8716
$\sigma_r(s_t^{\text{vol}}=1)$	I-G	0.15	0.10	0.2658	0.2250	0.3619	0.2654	0.2188	0.3524
$\sigma_r(s_t^{\text{vol}}=2)$	I-G	0.15	0.10	0.0438	0.0351	0.0565	0.0437	0.0355	0.0563
$\sigma_{\pi,t}$	U	0.075	0.0433	0.0341	0.0283	0.0895	0.0322	0.0210	0.0684
$p_{1,1}^{\text{mp}}$	B	0.95	0.03	0.9950	0.9399	0.9993	0.9947	0.9227	0.9998
$p_{2,2}^{\text{mp}}$	B	0.95	0.03	0.9932	0.9340	0.9961	0.9925	0.9315	0.9980
$p_{1,1}^{\text{vol}}$	B	0.90	0.10	0.9404	0.8202	0.9815	0.9396	0.8270	0.9792
$p_{2,2}^{\text{vol}}$	B	0.90	0.10	0.9671	0.9301	0.9874	0.9669	0.9294	0.9877

TABLE 4. Prior and posterior of the models $\mathfrak{M}_{\text{mp+vol}}$ and $\mathfrak{M}_{\text{(freq+mp)+vol}}$. N stands for Normal, B Beta, G for Gamma, I-G for Inverted-Gamma and U for Uniform distributions. The 5 percent and 95 percent demarcate the bounds of the 90 percent probability interval.

VIII. Figures

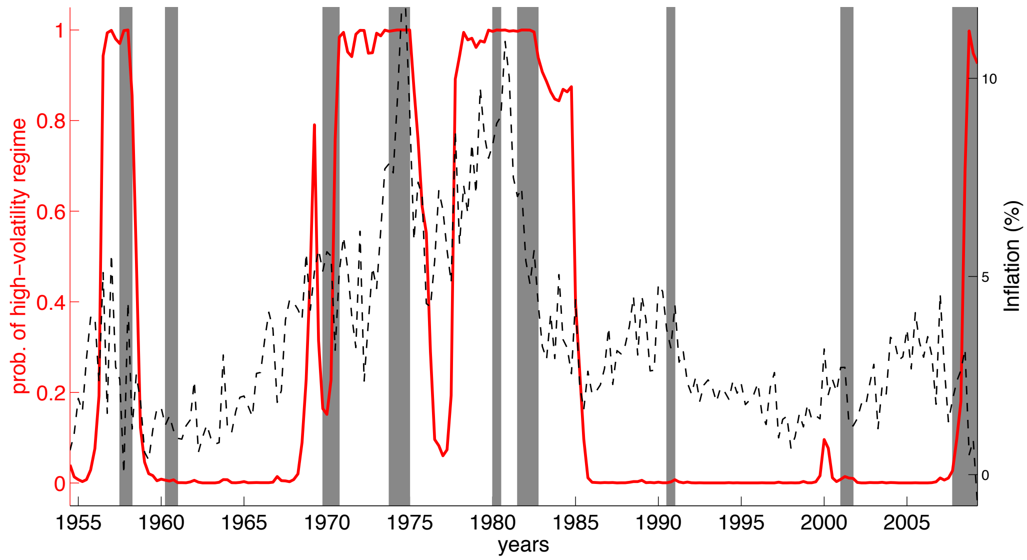

Figure 1a. Sample period: 1954.Q3–2009.Q2. Posterior probabilities of the "high-volatility" regime of the model $\mathfrak{M}_{\text{freq+vol}}$ (on the left scale, solid line) and actual inflation data (on the right scale, dotted line). The shaded grey area represents the NBER recessions.

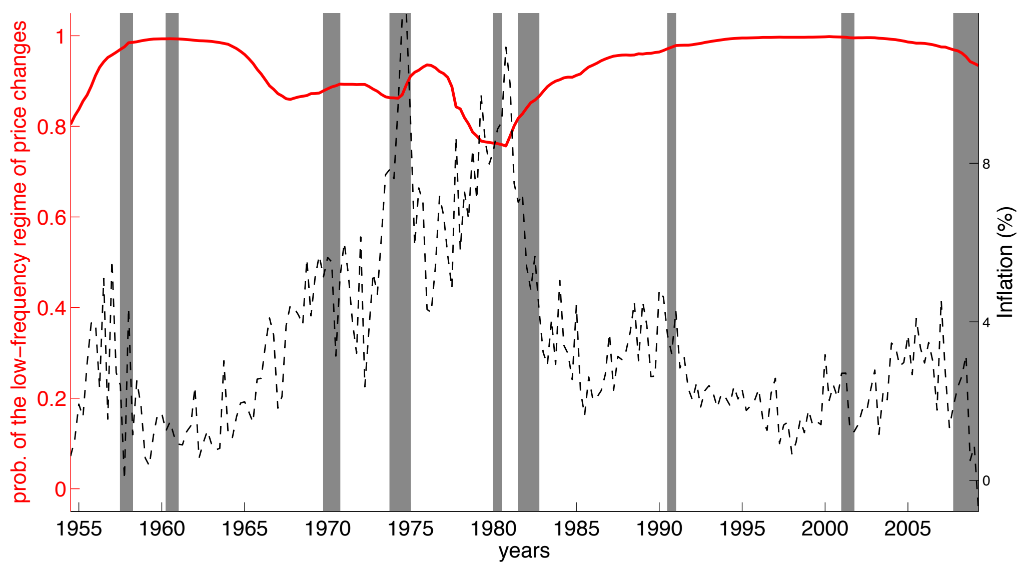

Figure 1b. Sample period: 1954.Q3–2009.Q2. Posterior probabilities of the "low frequency" regime of price changes for the model $\mathfrak{M}_{\text{freq+vol}}$ (on the left scale, solid line) and actual inflation data (on the right scale, dotted line). The shaded grey area represents the NBER recessions.

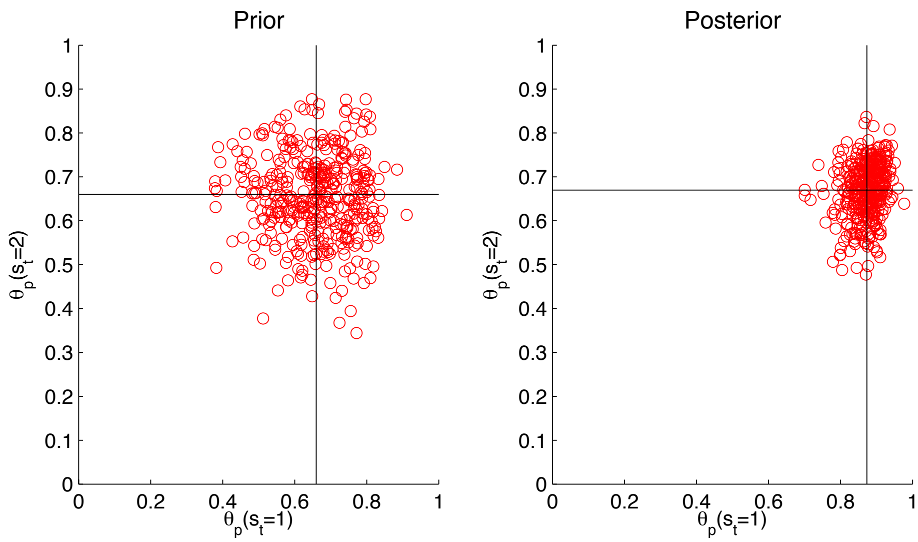

FIGURE 2. 400 draws from the prior (the left panel) and the posterior (the right panel) distributions of the model $\mathfrak{M}_{\text{freq}}$. Intersections of black lines mean posterior mode values.

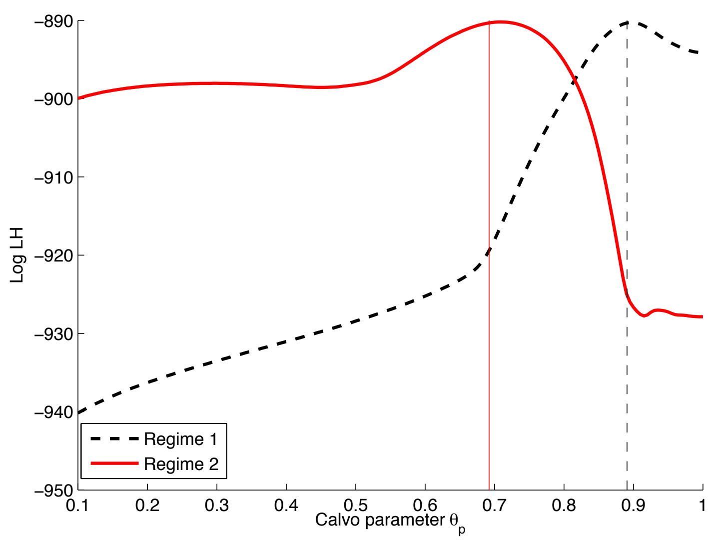

FIGURE 3. The log-likelihood as a function of the Calvo parameter (θ_p) of the model $\mathfrak{M}_{\text{freq}}$ under Regime 1 (“low-frequency”) in dotted black line and under Regime 2 (“high-frequency”) regime in solid red line.

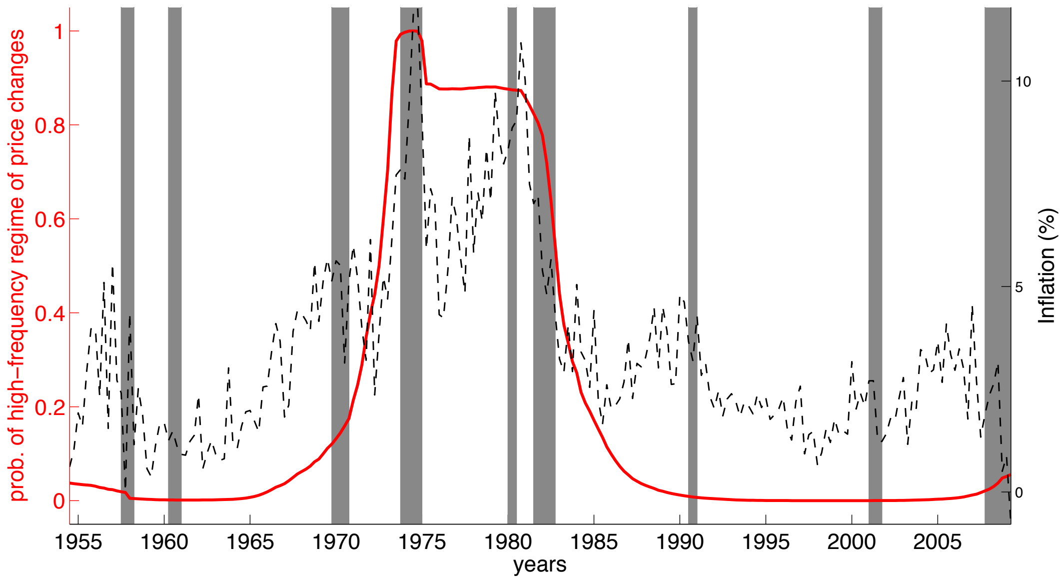

FIGURE 4. Sample period: 1954.Q3–2009.Q2. Posterior probabilities of the "high-frequency" regime of price changes of the model $\mathfrak{M}_{\text{freq}}$ (on the left scale, solid line) and actual inflation data (on the right scale, dotted line). The shaded grey area represents the NBER recessions.

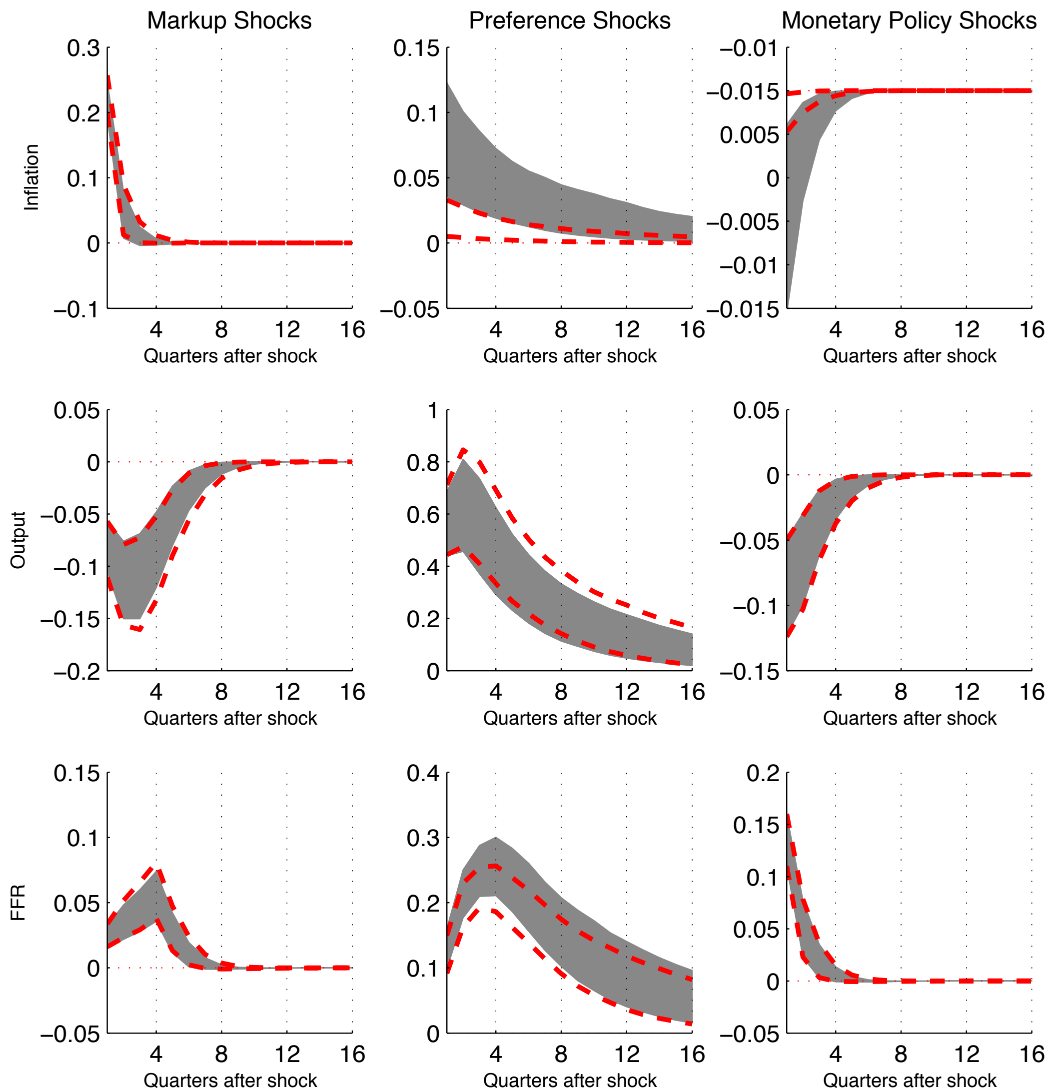

FIGURE 5. Impulse responses of inflation, output and the Federal Funds Rate (FFR) to the markup shock, preference shock, and monetary policy shock of the model $\mathfrak{M}_{\text{freq}}$. The shaded grey area represents the 0.90 percent error bands under the "low-frequency" regime and the dotted black lines represent those under the "high-frequency" regime.

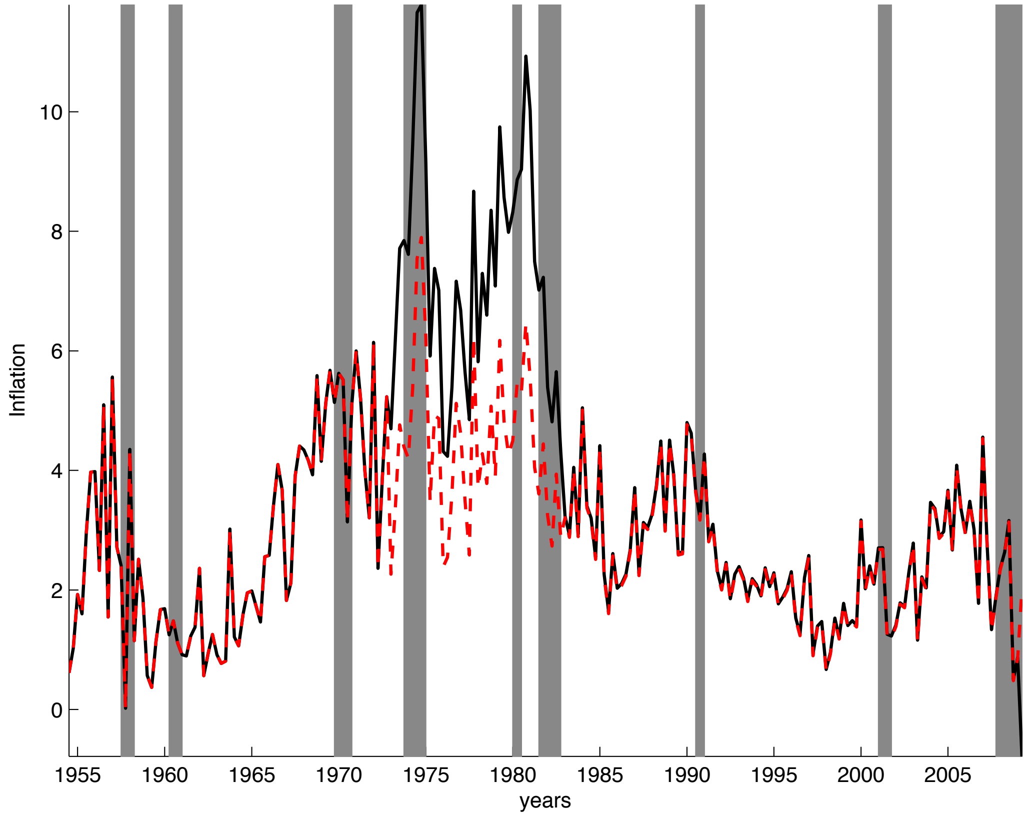

FIGURE 6. Sample period: 1954.Q3–2009.Q2. "Low-frequency" Regime throughout. The graph shows the actual path (black line) and the counterfactual path (red line). The shaded grey area represents the NBER recessions.

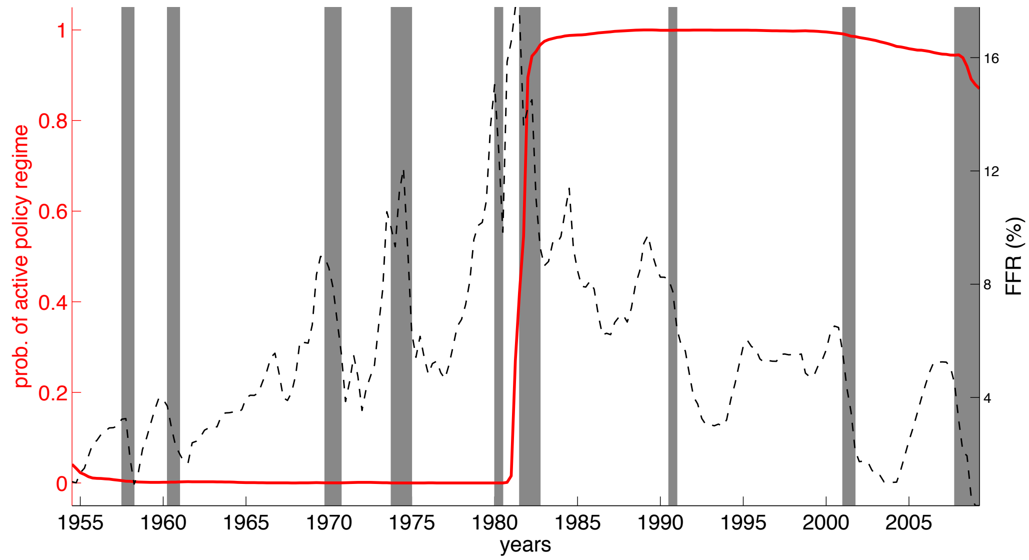

FIGURE 7A. Sample period: 1954.Q3–2009.Q2. Posterior probabilities of the "active policy" regime of the model $\mathfrak{M}_{\text{mp+vol}}$ (on the left scale, solid line) and actual FFR data (on the right scale, dotted line). The shaded grey area represents the NBER recessions.

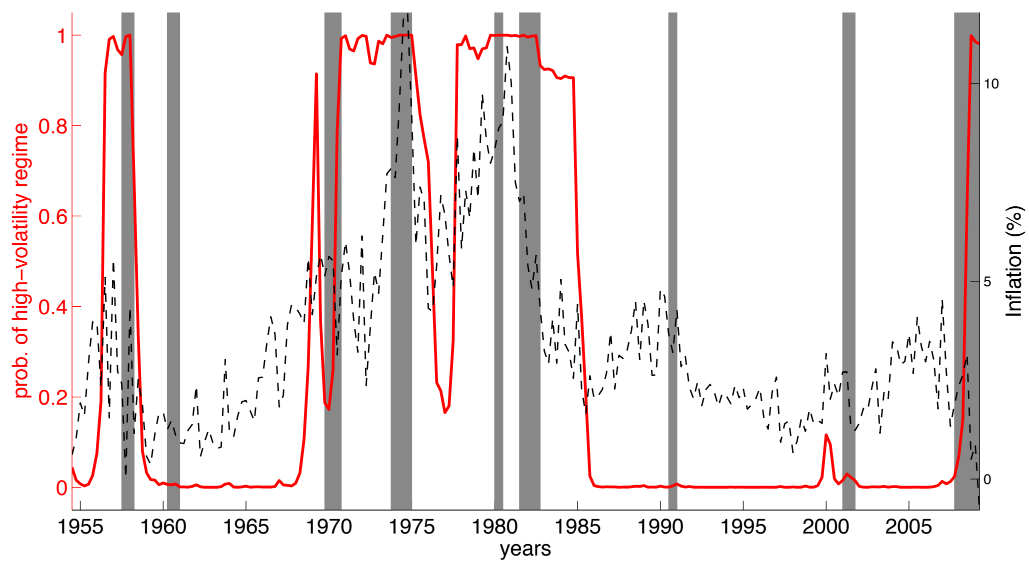

FIGURE 7B. Sample period: 1954.Q3–2009.Q2. Posterior probabilities of the "high-volatility" of the model $\mathfrak{M}_{\text{mp+vol}}$ (on the left scale, solid line) and actual inflation data (on the right scale, dotted line). The shaded grey area represents the NBER recessions.