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FREQUENCY OF PRICE ADJUSTMENTS:
NEW FACTS ABOUT PRICES

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FREQUENCY OF PRICE ADJUSTMENTS:
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By

Margarita Zabelina
Ms. Fin., University of Tampa, 2009

Advisor: Tao Zha, Ph.D.

An abstract of
A dissertation submitted to the Faculty of the
James T. Laney School of Graduate Studies of Emory University
in partial fulfillment of the requirements for the degree of
Doctor of Philosophy
in Economics
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Abstract

FREQUENCY OF PRICE ADJUSTMENTS:
NEW FACTS ABOUT PRICES
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I examine frequency of price adjustments using aggregate and micro data. In the first part I examine stability of Calvo pricing. 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. In the second part, using Mexican CPI data from 1994 to 2002 covering the period of large peso devaluation, I document a number of novel facts: First, the duration of prices differs between categories of goods and across economic conditions. Frequency of price adjustments and rankings of categories of goods by these frequency in Mexico differs from those in U.S. Second, a large shock to the firms marginal cost increases the frequency of price adjustments for all goods. This increase is particularly large for goods with a very stable price history. Third, frequency of price adjustments of nondurables and services increases with increase in market and firm's elasticity of demand. This relationship is opposite for durables. Standard ways of modeling frequency of price adjustments do not support these findings.

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CHAPTER 1

On the stability of Calvo-style Price-Setting Behavior

Stéphane Lhuissier

Margarita Zabelina

Chapter 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.

[1]

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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 (2008a) show that only the frequency of price increases covaries strongly with inflation. More recently, **?** 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[2] 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).

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.

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

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

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

where $\Pi_{t,t+s}^p = \Pi_{\nu=1}^s \pi^{1-\gamma_p} \pi_{t+\nu-1}^{\gamma_p}$ 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

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

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

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

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. Appendix 1.A 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[3] proposed in Farmer, Waggoner, and Zha (2009), Farmer, Waggoner, and Zha (2011) and Cho (2012).[4] In particular, we employ the algorithm solution of Farmer, Waggoner, and Zha (2011) to obtain the solution of the Markov-switching rational expectations model. See Appendix 1.A 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

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

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

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

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

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 ($\mathrm{FFR}_t^{\mathrm{Data}}$).[5] A detailed description of the data is provided in Appendix 1.B. The series are also reported in Figure 1. We stack this data in the following vector of observable variables:

$$y_t = [\triangle \ln \mathrm{Y}_t^{\mathrm{Data}}, \pi_t^{\mathrm{Data}}, \mathrm{FFR}_t^{\mathrm{Data}}]' \tag{22}$$

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

$$y_t = a + Hf_t \tag{23}$$

where

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

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 Appendix 1.A provides this technique to evaluate the likelihood and, therefore the posterior distribution.

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

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

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 (28). 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$^{\text{th}}$ 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. Appendix 1.C 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, $\mathfrak{M}_{\text{freq+vol}}$. 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 (28) 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[6], can change over time according to an independent Markov-switching process $s_t^{\mathrm{vol}} = 1, 2$ — "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

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

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 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 2a 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 2b, 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[7] in the sense

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

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.

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 [Bils and Klenow (2004)]. However, the "high-frequency" regime corresponds to a price duration around 3 quarters and corroborates with the finding of Bils and Klenow (2004).

Figure 3 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 4 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 5 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 6 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 7 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 (2008a), 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 $\mathfrak{M}_{(\text{freq+mp})+\text{vol}}$. 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 [Bils and Klenow (2004)].

Figures 8a and 8b 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

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

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 $\mathfrak{M}_{\text{(freq+mp)+vol}}$. 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, $\mathfrak{M}_{\text{(freq+mp)+vol}}$, 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.

1.A. Markov-switching DSGE model: Solution and Estimation

1.A.1. Log-linearization. The log-deviations of the stationary variable ζ_t from its steady state value is denoted $\hat{\zeta}_t$ and defined as $\hat{\zeta}_t = log\zeta_t - log\zeta$, except for $\hat{z} \equiv z_t - \gamma$.

A log-linear approximation of the solution to the firms' price-setting problem (12) is expressed as follows

$$\hat{\pi}_t = \frac{\beta}{1+\gamma_p\beta}\mathrm{E}_t\hat{\pi}_{t+1} + \frac{\gamma_p}{1+\gamma_p\beta}\hat{\pi}_{t-1} + \frac{(1-\theta_p\beta)(1-\theta_p)}{\theta_p(1+\gamma_p\beta)}\hat{w}_t + \hat{\theta}_t \tag{28}$$

This above equation, known as the New-Keynesian Phillips Curve (NKPC), relates the current inflation to the lagged inflation $\tilde{\pi}_{t-1}$, the expected inflation rate $\mathrm{E}_t\tilde{\pi}_{t+1}$, and the real marginal cost $\tilde{s}_t$. The last block of parameters $\kappa = \frac{(1-\theta_p\beta)(1-\theta_p)}{\theta_p(1+\gamma_p\beta)}$ is widely interpreted as the slope of the Phillips curve; i.e., a measure of nominal rigidity. It is worth noting that this slope is inversely correlated with the parameter that determines the frequency of price changes, θ_p.

The other log-linearized equilibrium conditions are as follows

$$\begin{aligned}\hat{\lambda}_t =& \frac{h\beta e^{\gamma}}{(e^{\gamma}-h\beta)(e^{\gamma}-h)}E_t\hat{y}_{t+1} - \frac{e^{\gamma 2}+h^2\beta}{(e^{\gamma}-h\beta)(e^{\gamma}-h)}\hat{y}_t + \frac{he^{\gamma}}{(e^{\gamma}-h\beta)(e^{\gamma}-h)}\hat{y}_{t-1} \\ &+ \frac{h\beta e^{\gamma}\rho_z - he^{\gamma}}{(e^{\gamma}-h\beta)(e^{\gamma}-h)}\hat{z}_t + \frac{e^{\gamma}-h\beta\rho_b}{(e^{\gamma}-h\beta)}\hat{b}_t \end{aligned} \tag{29}$$

$$\hat{\lambda}_t = \hat{R}_t + E_t\left(\hat{\lambda}_{t+1} - \hat{\pi}_{t+1}\right) - \rho_z\hat{z}_t \tag{30}$$

$$\hat{w}_t = \eta\hat{y}_t + \hat{b}_t - \hat{\lambda}_t \tag{31}$$

where (29) is the marginal utility equation with $\hat{\lambda}_t$ denoting the marginal utility of consumption; (30) is the Euler equation; and (31) is the labor supply equation. The monetary policy rule is given by

$$\tilde{R}_t = \rho_R \tilde{R}_{t-1} + (1-\rho_R)\left[\psi_\pi(\tilde{\pi}_{4,t} - \tilde{\pi}_t^*) + \psi_y\left(\tilde{y}_t - \tilde{y}_t^*\right)\right] + \varepsilon_{R,t} \tag{32}$$

where $\tilde{y}_t^*$ denotes the output of the economy with flexible prices. The equations (28), (29), (30), (31), and (32) describe the evolution of the economy conditional on the stochastic processes for the shocks $\hat{x}_t = \rho_x \hat{x}_t + \varepsilon_{x,t}$, with $x \in \{z, \theta, b, \pi^*\}$. The stochastic process for monetary policy has already been specified in (32).

1.A.2. Solution method. The solution proposed by Cho (2011) exploits the idea of the forward method for solving MS-DSGE models whereas the method by Farmer, Waggoner, and Zha (2009) and Farmer, Waggoner, and Zha (2011) exploit Newton's method to find all possible Minimum State Variable (MSV) solutions. When the model is determinate, both methods return the same solution. Using the algorithm solution of Farmer, Waggoner, and Zha (2011), we obtain the solution of the Markov-switching rational expectations model in the following way

$$f_t = V(s_t)F_1(s_t)f_{t-1} + V(s_t)G_1(s_t)\varepsilon_t \tag{33}$$

where

$$\begin{bmatrix} A(i)V(i) & \Pi \end{bmatrix} \begin{bmatrix} F_1(i) \\ F_2(i) \end{bmatrix} = B(i) \qquad \begin{bmatrix} A(i)V(i) & \Pi \end{bmatrix} \begin{bmatrix} G_1(i) \\ G_2(i) \end{bmatrix} = \Psi(i) \tag{34}$$

and

$$\left(\sum_{i=1}^{h} p_{i,j} F_2(i) \right) V(j) = 0 \tag{35}$$

We find an MSV equilibrium by finding the matrices V_i, then the matrices $F_{1,i}$, $F_{2,i}$, $G_{1,i}$, and $G_{2,i}$. If equation (35) is satisfied, we obtain a MSV equilibrium.

1.A.3. Constructing the posterior distribution. To form the posterior density, denoted $p(\theta|Y_T)$, we combine the overall likelihood function $p(Y_T|\theta)$ with the prior $p(\theta)$

$$p(\theta|Y_T) \propto p(Y_T|\theta)p(\theta) \tag{36}$$

where θ contains all the parameters. The evaluation of the overall likelihood function is obtained using the Kim and Nelson (1999) filter, which is a combination of the Kalman filter and the Hamilton (1989) filter. Let $p(y_t|s_t, s_{t-1}, \psi_{t-1}, \theta)$ the conditional likelihood function given s_t, s_{t-1} and the past information ψ_{t-1}. By integrating s_t and s_{t-1} out, the likelihood function at date] t is as follows

$$p(y_t|\psi_{t-1}, \theta) = \sum_{s_t} \sum_{s_{t-1}} p(y_t|s_t, s_{t-1}, \psi_{t-1}, \theta) \mathrm{Pr}[s_t, s_{t-1}|\psi_{t-1}] \tag{37}$$

with

$$\mathrm{Pr}[s_t, s_{t-1}|\psi_{t-1}] = \mathrm{Pr}[s_t|s_{t-1}]\mathrm{Pr}[s_{t-1}|\psi_{t-1}] \tag{38}$$

where $\Pr[s_t|s_{t-1}]$ is the transition probability described previously. We then update the joint probability term in the following way

$$\Pr[s_t, s_{t-1}|\psi_t] = \frac{f(y_t, s_t, s_{t-1}|\psi_{t-1})}{f(y_t|\psi_{t-1})} = \frac{f(y_t|s_t, s_{t-1}, \psi_{t-1})\Pr(s_t, s_{t-1}|\psi_{t-1})}{f(y_t|\psi_{t-1})} \tag{39}$$

and finally obtain the probability term given the information at date t

$$\Pr[s_t|\psi_t] = \sum_{s_{t-1}} \Pr[s_t, s_{t-1}|\psi_{t-1}] \tag{40}$$

The conditional likelihood function, $p(y_t|s_t, s_{t-1}, \psi_{t-1})$, cannot be evaluated with the standard Kalman filter. If in the constant case, the updated forecasts of the unobserved state vector, β_t, and the updated mean squared error of forecast P_t depend only on the information set ψ_t, in a case with Markov switching elements, these forecasts are also conditioned on the unobserved state $s_t = j$ and $s_{t-1} = i$. It follows that, at each iteration, the number of β_t and P_t to consider increases, which makes the Kalman filter unfeasible. In each step, we then collapse these h^2 terms in order to make the evaluation feasible. This approximation allows to make inference on β_t based on information ψ_{t-1}, given only s_{t-1}. See Kim and Nelson (1999) for more details. The overall likelihood is

$$p(Y_T|\theta) = \prod_{t=1}^{T} p(y_t|\psi_{t-1}, \theta) \tag{41}$$

Once the parameters of the model are estimated, we follow Kim (1994) and Kim and Nelson (1999) and make inference on s_T, $(t = 1, ..., T)$, the smoothed probabilities, in the following way

$$\Pr[s_t = j|\psi_T] = \sum_{k=1}^{M} \Pr[s_t = j, s_{t+1} = i|\psi_T] \tag{42}$$

where

$$\Pr[s_t = j, s_{t+1} = i|\psi_T] = \frac{\Pr[s_{t+1} = i|\psi_t].\Pr[s_t = j|\psi_t].\Pr[s_{t+1} = i|s_t = j]}{\Pr[s_{t+1} = i|\psi_t]} \tag{43}$$

The advantage of such a method is that it allows us to infer the unobservable variable s_t using all the information in the sample.

1.B. Data

The data used for estimation includes quarterly data from the third quarter of 1954 to the second quarter of 2009. Inflation π_t is the first log-difference of the GDP deflator; the nominal interest rate R_t is the Federal Funds rate; and the output growth Δy_t is the first log-difference of real per capita GDP. This latter is obtained by dividing real GDP (GDPC96) by population (LF and LH). All data comes from the St. Louis Federal Reserve Bank database (FRED). The series are reported in Figure 1.

1.C. Marginal Data Densities

In Bayesian analysis, Marginal Data Density (MDD) is a tool commonly used for comparison between models. The general idea behind this is as follows: We know that posterior density can be written as

$$P(\theta|Y) = \frac{P(Y|\theta)P(\theta)}{P(Y)} \tag{44}$$

We know that true posterior is

$$\int P(\theta|Y)d\theta = 1 \tag{45}$$

which makes

$$\int P(Y|\theta)P(\theta)d\theta = P(Y) \tag{46}$$

and if we use some proposal density $P_{prop}(\theta)$ which integrates to 1 we can deduce that

$$\int \frac{P_{prop}(\theta)}{P(Y|\theta)P(\theta)} \frac{P(Y|\theta)P(\theta)}{P(Y)} d\theta = \frac{1}{P(Y)} \tag{47}$$

we can define $m(\theta) = \frac{P_{prop}(\theta)}{P(Y|\theta)P(\theta)}$ and since we know that $\frac{P(Y|\theta)P(\theta)}{P(Y)} d\theta = P(\theta|Y)$ and is true density integrating to 1 we can conclude that

$$\frac{1}{P(Y)} = \sum_{i=0}^{\infty} m(\theta_i) \tag{48}$$

The closer proposed density is to posterior kernel, more accurate results are obtained. In addition when one looks at the formulas, it is clear that the higher marginal data density, the closer estimated posterior is to the "true" posterior. Thus it allows us to compare models in a most efficient way.

1.C.1. Geweke (1999) method. We follow Geweke method for our first calculation and choose $P_{prop}(\theta)$ to be truncated Normal. First, we run a random-walk

Metropolis-Hastings algorithm and generate a significant number of posterior draws θ_t. Using twenty percent of these draws, we compute certain statistics, such as mode $\hat{\theta}$ for each estimated parameter and the analogue of the variance-covariance matrix, we center it around $\hat{\theta}$ instead of the mean.

$$V = \frac{1}{T}\sum_{t=1}^{T}(\theta_t - \hat{\theta})(\theta_t - \hat{\theta})' \tag{49}$$

The reason for this choice of centering is the fact that in the Markov-switching world mean is often located in a low probability region. It stands to reason that if everything is centered around the mean truncation used for this method, it would cut "too much" of the distribution when creating proposal distribution. Thus most of the posterior draws would fall within the zero-probability region of posterior distribution.

After we obtain these statistics, we create proposal density using truncated Normal centered around $\hat{\theta}$ and scaled by $V^{(-1)}$ Using the rest of the posterior draws, we evaluate posterior and proposal densities at these draws, obtaining $P_{post}(\theta)$ and $P_{prop}(\theta)$. Using these values, we proceed by computing

$$MDD = \frac{1}{T}\sum_{t=1}^{T}(\frac{P_{prop}(\theta_t)}{P_{post}(\theta_t)}) \tag{50}$$

1.C.2. Waggoner and Zha (2008) method. Since in practice posteriors estimated for the parameters in a Markov-switching framework are often highly non-Gaussian, we are using a new modified harmonic mean method for proposed by Sims, Waggoner, and Zha (2008)calculations of MDD. We first proceed by generating posterior draws from the posterior distribution using the Random-Walk Metropolis-Hastings algorithm. We then make proposal draws from normal distribution as our model is fairly small and Gaussian approximation may give accurate results, even though in the original Sims, Waggoner, and Zha (2008) method elliptical distribution is used (it includes Gaussian density as a special case). The following procedure could be used for elliptical distribution:

$$g(\theta) = \frac{\Gamma(k/2)}{2\pi^{k/2}|det(\hat{S})|}\frac{f(r)}{r^{k-1}} \tag{51}$$

where Γ is a standard gamma function and $f(r)$ is a one-dimensional density defined on the positive reals. Calculations can be done in the following way:

(1) Calculate the statistics of posterior draws from a Metropolis-Hastings algorithm using 20percent of all draws (all other calculations are done using the remaining 80 percent of draws). For centering, we used posterior mode $\hat{\theta}$. Calculate scale $\hat{S} = \sqrt{\hat{\Omega}}$, where $\hat{\Omega}$ is a variance-covariance matrix and radius is

$$r^{(i)} = \sqrt{(\theta^{(i)} - \hat{\theta})'\hat{\Omega}^{-1}(\theta^{(i)} - \hat{\theta})} \tag{52}$$

Using this radius, calculate other statistics:

- c_1 such that 1 percent of $r^i \leq c_1$
- c_{10} such that 10 percent of $r^i \leq c_{10}$ and
- c_{90} such that 90percent of $r^i \leq c_{10}$

From these statistics calculate parameters a, b and v

$$a = c_1 \qquad b = \frac{c_{90}}{0.9^{\frac{1}{v}}} \qquad v = \frac{\ln(1/9)}{\ln(c_{10}/c_{90})} \tag{53}$$

(2) Using these values, evaluate function $g(\theta)$ at posterior draws. It is calculated as:

$$f(r) = \begin{cases} \frac{vr(i)^{(v-1)}}{b^v - a^v} & \text{if } r^{(i)} \in (a, b) \\ 0 & \text{elsewhere} \end{cases} \tag{54}$$

(3) Calculate proposal draws from elliptical density and evaluate them at posterior density. First, simulate draws x from the standard normal distribution. Second, generate draw u identically and independently from the uniform distribution between $[0, 1]$. Then we form

$$r = (u(b^v - a^v) + a^v)^{\frac{1}{v}} \tag{55}$$

Using these x and r we calculate proposal draws

$$\theta_{proposal} = \frac{r}{||x||}\hat{S}x + \hat{\theta} \tag{56}$$

where x is the random normal and evaluate posterior at these draws.

(4) One can calvulate the weighting function in the same way for any proposal dencity used.

$$h(\theta) = \frac{\chi_{\Theta_L}(\theta)}{q_L} g(\theta) \tag{57}$$

is a truncated proposal distribution. Truncation is done using $\hat{q}_L$, which is estimated as probability that the posterior evaluated at proposal draws falls within the region:

$$\Theta_L = \{\theta : p(Y_t|\theta)p(\theta) \geq L\} \tag{58}$$

$\chi_{\Theta_L}(\theta)$ is an indicator function, which is equal to 1 when posterior density evaluated at posterior draw falls within Θ_L and 0 otherwise. From here we can assess the overlap between posterior density and weighting function and calculate the marginal likelihood:

$$p(Y_T)^{-1} = \int_{\Theta} \frac{h(\theta)}{p(Y_t|\theta)p(\theta)} p(\theta|Y_T)d(\theta) \tag{59}$$

Defining $m(\theta)=\frac{h(\theta)}{p(Y_t|\theta)p(\theta)}$ and using the Monte Carlo integration, we get

$$\hat{p}(Y_T)^{-1} = \frac{1}{N}\sum_{i=1}^{N} m(\theta^{(1)}) \tag{60}$$

In order to check the robustness of our conclusions based on this methodology, we also use the truncated normal method proposed by Geweke (1999) and find that even though magnitudes of MDD are different, the rankings of the models stay the same.

We are using the procedure described above for truncation; however instead of an eliptical distribution, we are using a normal distribution.

1.C.3. Bridge method. Meng and Wong (1996) propose a generalization of the importance sampling method; the so-called “bridge sampling”. This technique combines the Markov Chain Monte Carlo (MCMC) draws from the posterior probability density function (pdf) with the draws from the weighting function (or importance density) through a bridge function $\alpha(.)$ that reweighs both functions. Their method is based on the following result:

$$p(Y_T) = \frac{\mathrm{E}_q(\alpha(\theta)p^*(\theta))}{\mathrm{E}_p(\alpha(\theta)h(\theta))} \tag{61}$$

where $\alpha(\theta)$ is an arbitrary function and $p^*(\theta)$ the posterior kernel such that $p^*(\theta|Y_t) = p(Y_T|\theta)p(\theta)$.

It follows that the estimator $[\hat{p}(Y_T)]$ is called the general bridge sampling estimator

$$\hat{p}(Y_T) = \frac{\frac{1}{N_p}\sum_{j=1}^{N_p} \alpha(\theta^j)p^*(\theta^{(j)})}{\frac{1}{N_h}\sum_{i=1}^{N_p} \alpha(\theta^i)h(\theta^{(i)})} \tag{62}$$

where N_h is the number of draws from the weighting density and N_p is the number of draws from the posterior distribution.

Once all draws from the importance density $h(\theta)$ and MCMC draws from the posterior density $p(\theta|Y_T)$ have been made, one can easily calculate $\hat{p}(Y_T)$. Meng and Wong (1996) proposes the following bridge function:

$$\alpha(\theta) \propto \frac{1}{N_h h(\theta) + N_p p(\theta|Y_T)} \tag{63}$$

1.D. Tables

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.

	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

		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.

1.E. Figures

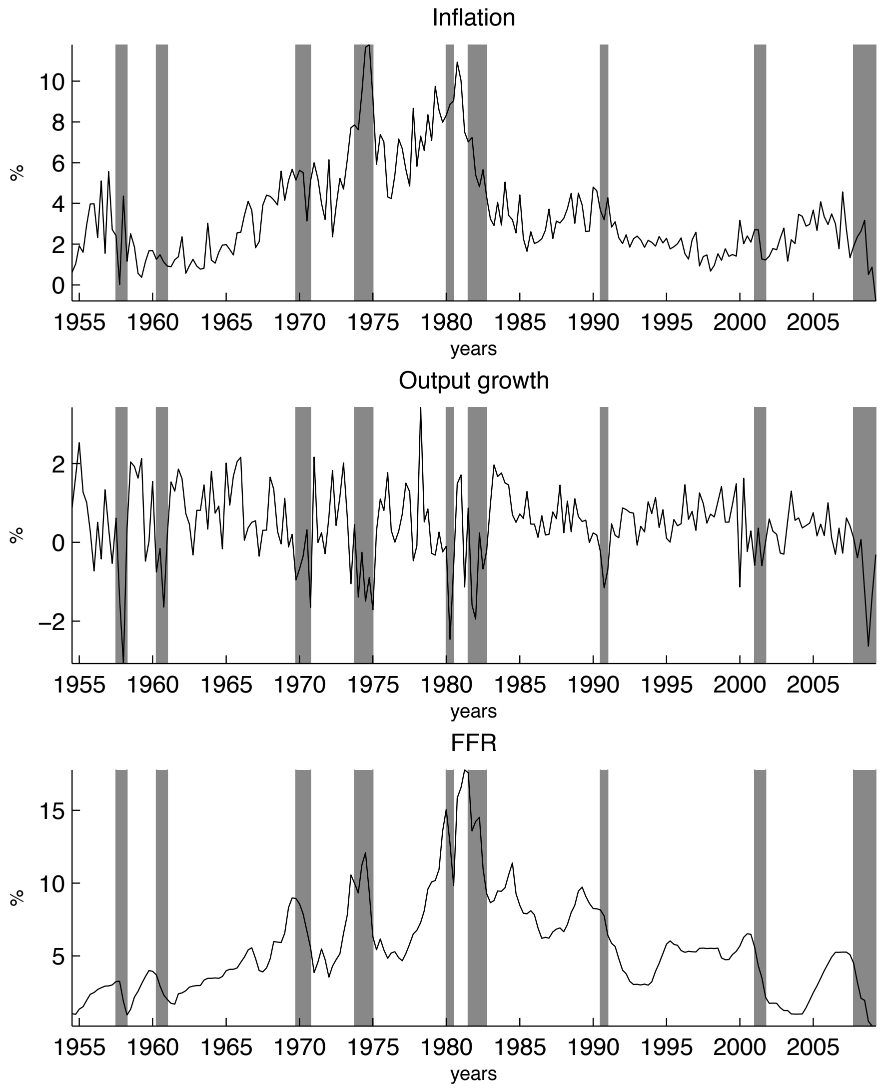

FIGURE 1. Sample period: 1954.Q3-2009.Q2. The shaded grey columns denote the NBER recessions.

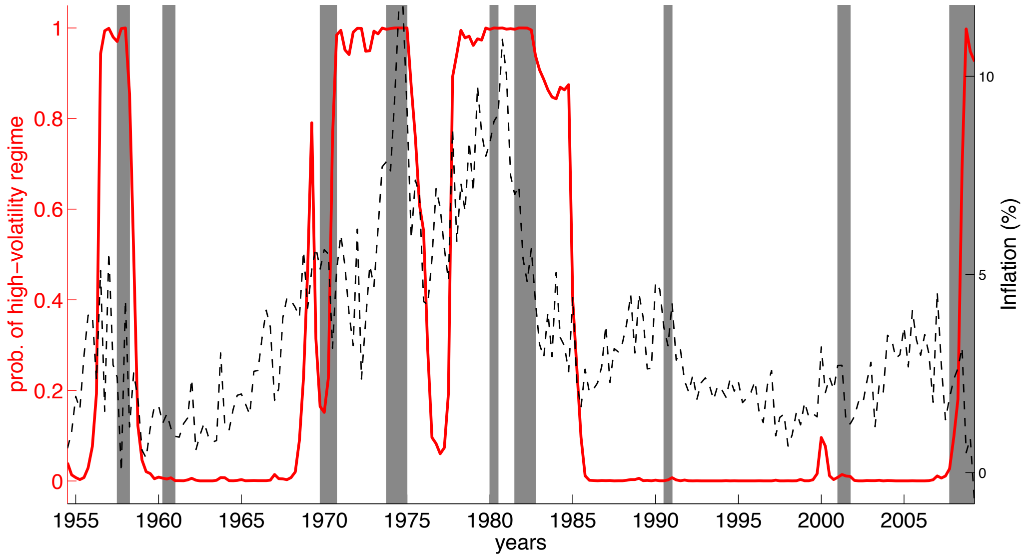

Figure 2a. Sample period: 1954.Q3–2009.Q2. Posterior probabilities of the "high-volatility" regime of the model $\mathfrak{M}_{\text{freq+vol}}$ (on the left scale, solid line) and actual inflation data (on the right scale, dotted line). The shaded grey area represents the NBER recessions.

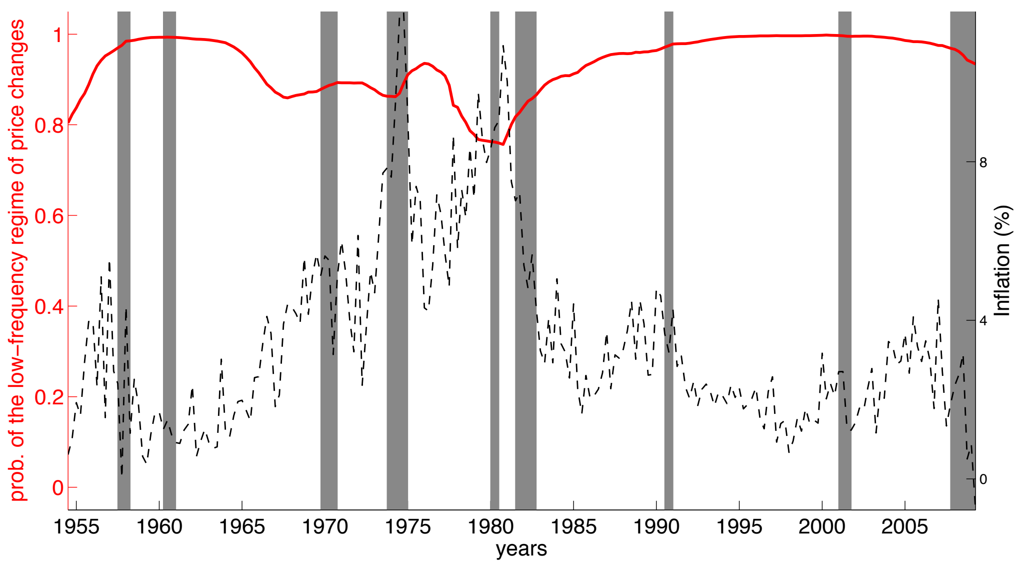

Figure 2b. Sample period: 1954.Q3–2009.Q2. Posterior probabilities of the "low frequency" regime of price changes for the model $\mathfrak{M}_{\text{freq+vol}}$ (on the left scale, solid line) and actual inflation data (on the right scale, dotted line). The shaded grey area represents the NBER recessions.

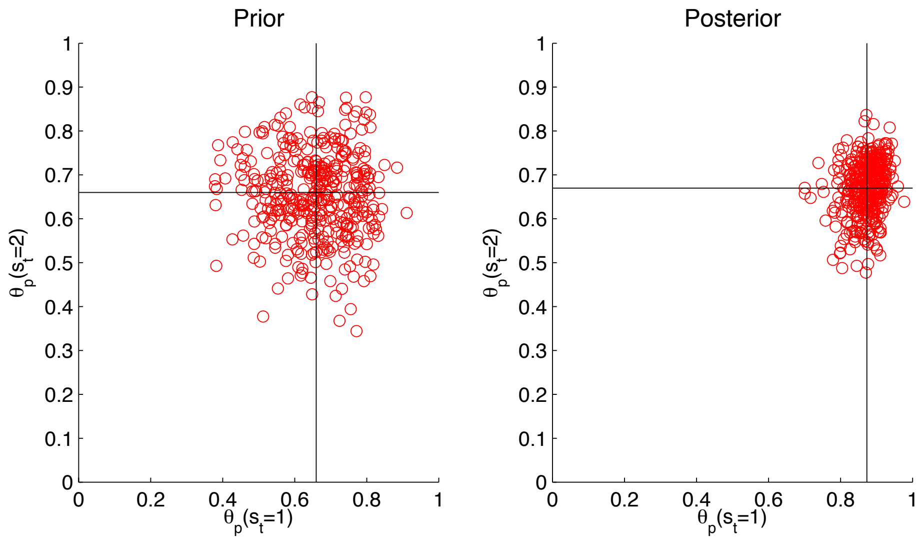

FIGURE 3. 400 draws from the prior (the left panel) and the posterior (the right panel) distributions of the model $\mathfrak{M}_{\text{freq}}$. Intersections of black lines mean posterior mode values.

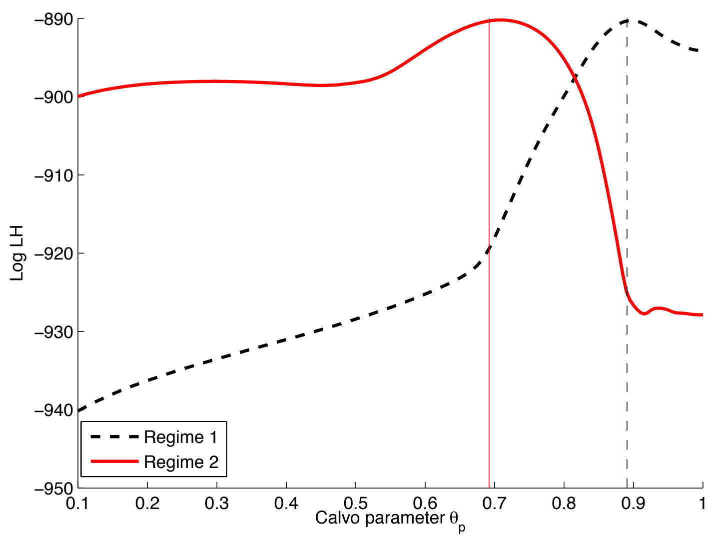

FIGURE 4. The log-likelihood as a function of the Calvo parameter (θ_p) of the model $\mathfrak{M}_{\text{freq}}$ under Regime 1 ("low-frequency") in dotted black line and under Regime 2 ("high-frequency") regime in solid red line.

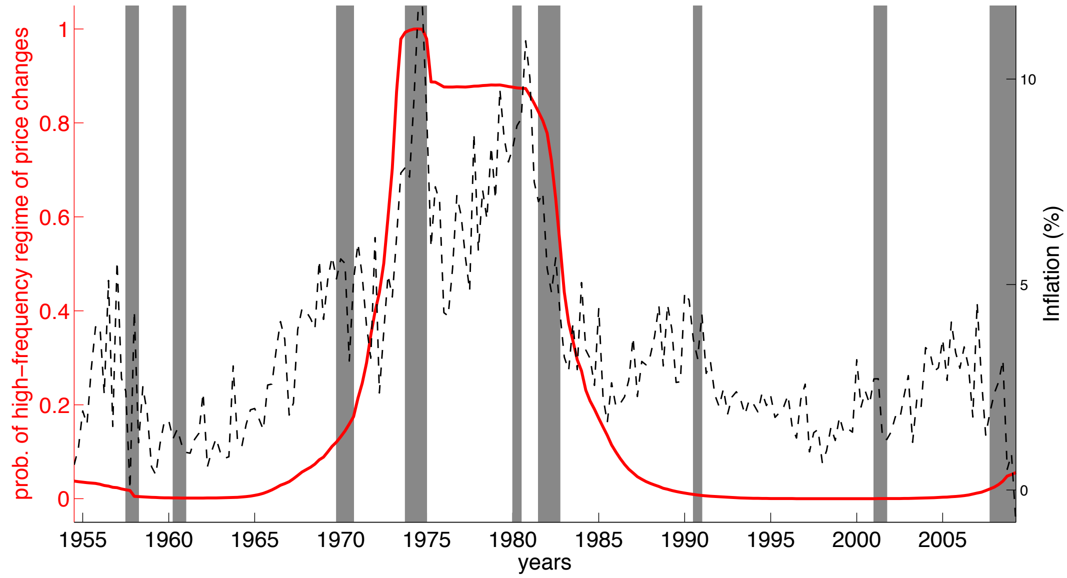

Figure 5. Sample period: 1954.Q3–2009.Q2. Posterior probabilities of the "high-frequency" regime of price changes of the model $\mathfrak{M}_{\text{freq}}$ (on the left scale, solid line) and actual inflation data (on the right scale, dotted line). The shaded grey area represents the NBER recessions.

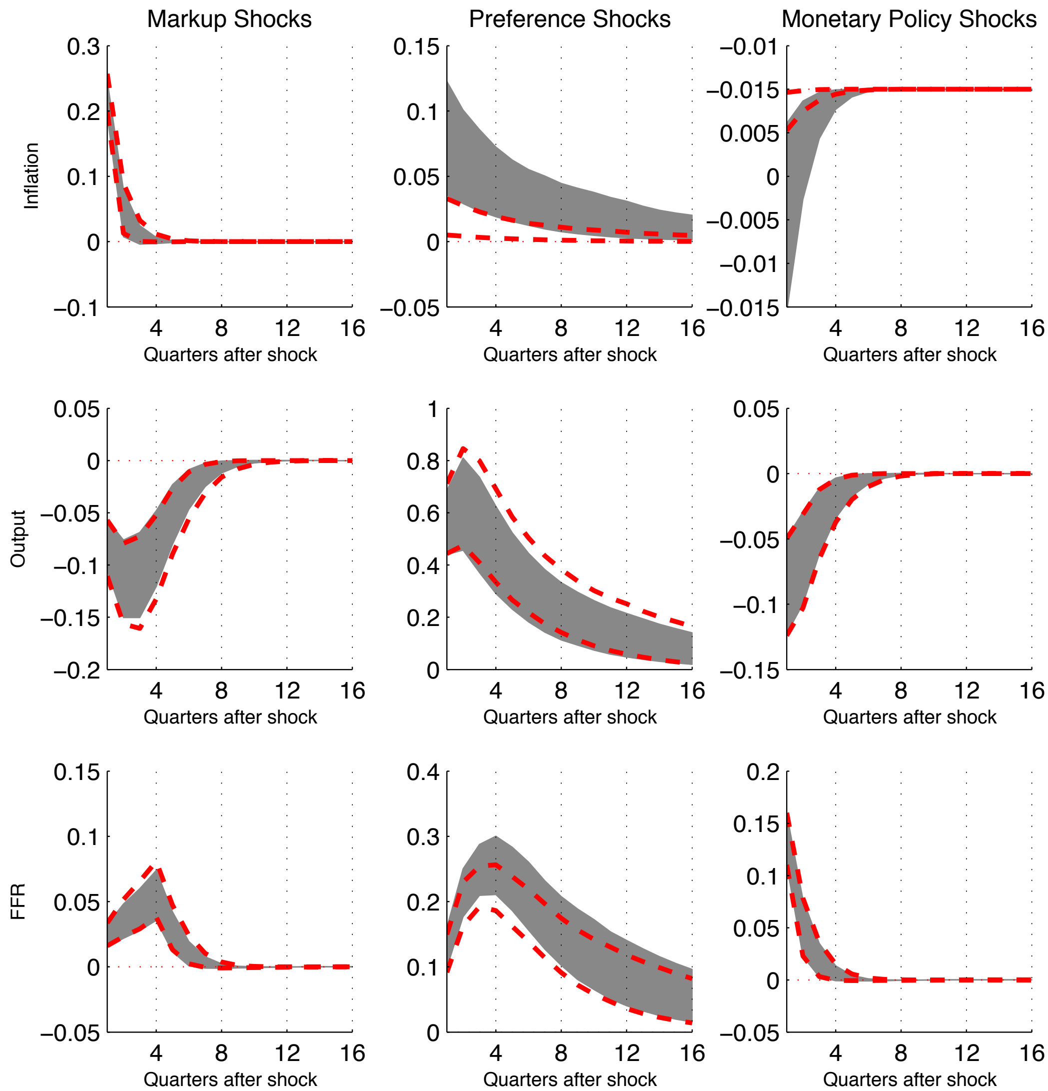

FIGURE 6. Impulse responses of inflation, output and the Federal Funds Rate (FFR) to the markup shock, preference shock, and monetary policy shock of the model $\mathfrak{M}_{\text{freq}}$. The shaded grey area represents the 0.90 percent error bands under the "low-frequency" regime and the dotted black lines represent those under the "high-frequency" regime.

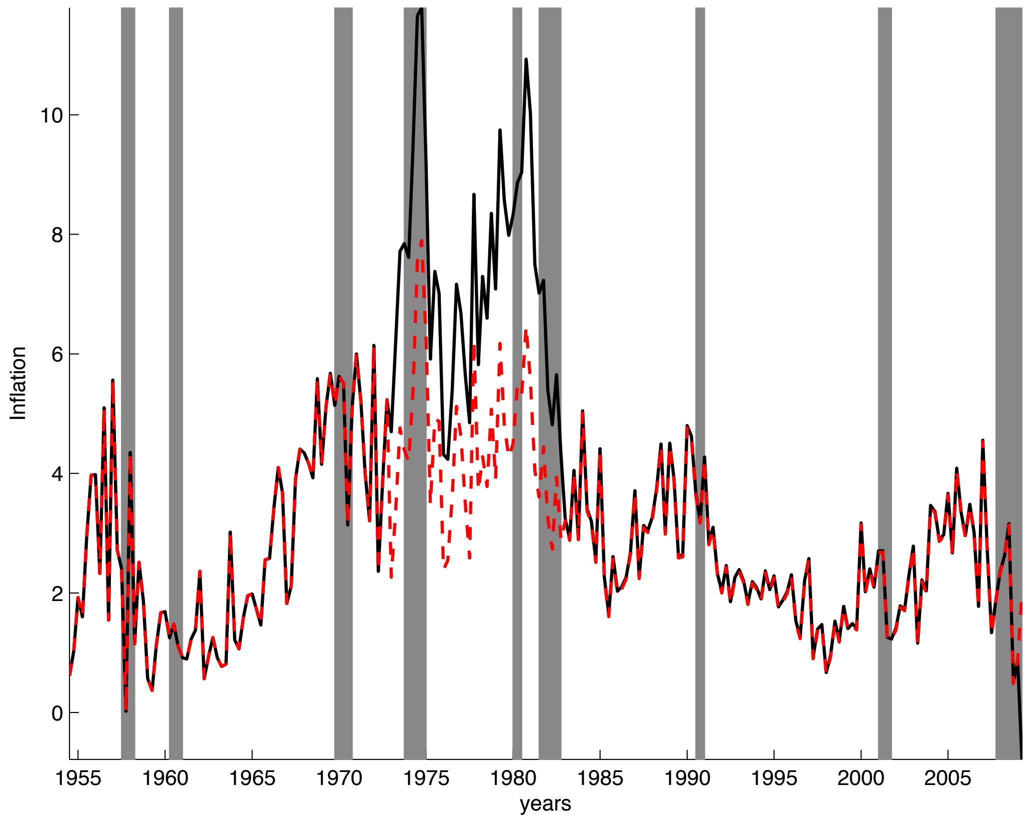

Figure 7. Sample period: 1954.Q3–2009.Q2. "Low-frequency" Regime throughout. The graph shows the actual path (black line) and the counterfactual path (red line). The shaded grey area represents the NBER recessions.

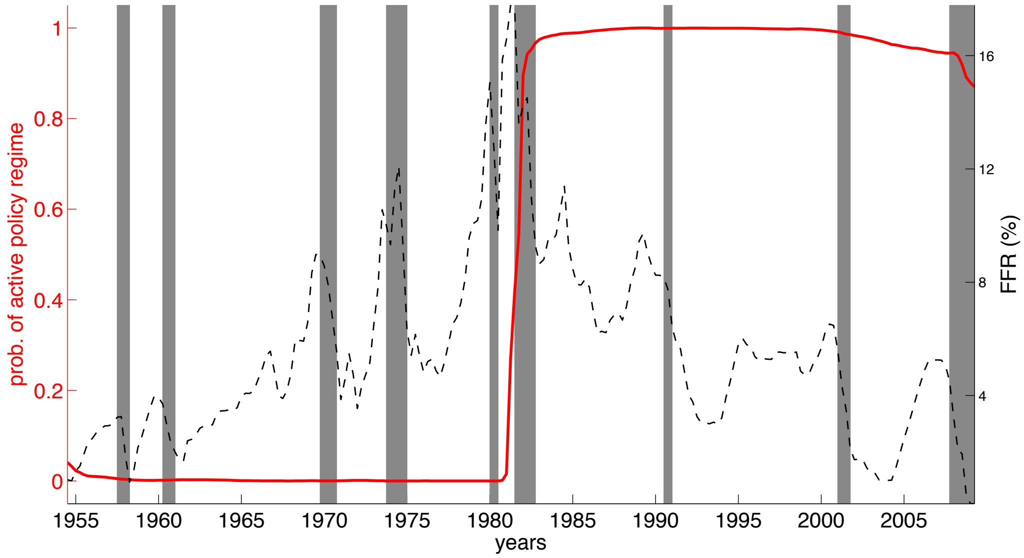

FIGURE 8A. Sample period: 1954.Q3–2009.Q2. Posterior probabilities of the "active policy" regime of the model $\mathfrak{M}_{\mathrm{mp+vol}}$ (on the left scale, solid line) and actual FFR data (on the right scale, dotted line). The shaded grey area represents the NBER recessions.

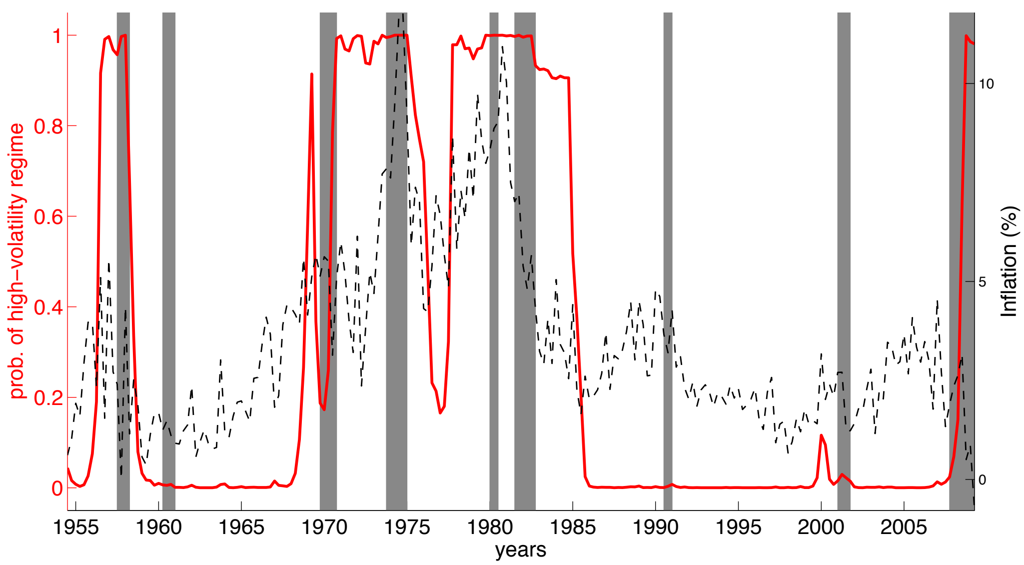

FIGURE 8B. Sample period: 1954.Q3–2009.Q2. Posterior probabilities of the "high-volatility" of the model $\mathfrak{M}_{\mathrm{mp+vol}}$ (on the left scale, solid line) and actual inflation data (on the right scale, dotted line). The shaded grey area represents the NBER recessions.

CHAPTER 2

Market power and the Frequency of Price Adjustments: New Facts from Mexico

Margarita Zabelina

Chapter Abstract

Using Mexican CPI data from 1994 to 2002, I document a number of novel facts. First, the duration of prices differs between categories of goods and across economic conditions while relative change in size of adjustments stays the same. Frequency of price adjustments and rankings of categories of goods by these frequencies in Mexico differ from those in U.S. Second, a large shock to the firms marginal cost increases the frequency of price adjustments for all goods. This increase is particularly large for goods with a very stable price history. Third, frequency of price adjustments of nondurables and services increases with increase in market and firm's elasticity of demand. This relationship is opposite for durables. Standard ways of modeling frequency of price adjustments do not support these findings.

I. Introduction

The frequency of price adjustments is one of the key factors driving changes in the overall price level and defining the degree of nominal rigidities. Nominal rigidities, in turn, are largely responsible for the incomplete pass-through of various shocks, movements in the real exchange rates, and inflation rates. Establishing the facts about frequency of price adjustments and understanding the mechanisms behind the price-setting behavior of the firms is crucial for the analysis of optimal monetary policy as well as of the welfare implications. It is also important to understand the differences in such behavior among the firms operating in different industries and in different economic circumstances. I use disaggregated monthly Mexican product-level CPI data from 1994-2002 to record, analyze, and contrast facts about the frequency of price adjustments in different economic conditions and among different categories of goods.

This data set is unique in covering the periods of time associated with high currency devaluation, large movements in real exchange rates, and high inflation as well as periods of time when the economy was relatively stable. It is important to note that the U.S. data that is usually used for the analysis of the frequency of price adjustments does not contain information on price-setting during and after the shocks to an economy as large as the shocks associated with Mexican tequila crisis of 1994.

This data set has been used by Gagnon (2009) to show that the frequency of price adjustments is correlated with inflation at high levels of inflation. Atkin, Faber, and Gonzalez-Navarro (2015) examine effects of foreign direct investment using the same data set. It has also been used to evaluate the impact of large exchange rate devaluations on the cost of living at different points of the income distribution (Cravino and Levchenko (2015)). I use the data to further explore the nature of changes in the price-setting behavior of firms. This analysis does not only look at the frequency of price adjustments across time, but also establishes mechanisms that influence these adjustments.

A number of facts concerning the frequency of price adjustments is recorded and the connection of these facts with existing theories of price-setting are investigated.

First, the data suggests that the frequency of price adjustments differs between various categories of goods. There are major differences between durables, non-durables and services across an entire sample with prices of the services adjusting less frequently (price duration of around 6 months) than those of durable goods (median price duration of around 5 months) and non-durable goods (price duration of 3 months). This is in line with Burstein, Eichenbaum, and Rebelo (2005a) and Burstein, Eichenbaum, and Rebelo (2005b) who examine differences in price adjustments between tradable and non-tradable goods. There are also differences in the frequencies of price adjustments among different categories of goods with apparel and food goods adjusting prices more often (at around 0.3, which corresponds to a price duration of 3 months) than those in the entertainment, medical expenses, transportation, and household supplies categories (around 0.15-0.2; price duration of around 6 months).

It is worth mentioning that price duration for different categories of goods in Mexico is different from duration established for the same categories in U.S. (Klenow and Malin (2010)). Rankings of the goods by price duration are also different. For example in U.S. nondurable goods adjust prices less frequently than durable goods.

Second, when the peso underwent a period of high devaluation in 1994, which was considered a sizable shock to the marginal cost of firms, the frequency of price adjustments increases for all categories of goods. Frequency of price adjustments for services increased by 150 percent, for durables by 110 percent and for nondurables by 85 percent. There are also differences in reaction to devaluation among goods divided using different classification. Goods in the apparel and food categories (the frequent adjusters) increase their frequency by about 50-60 percent while other categories (low frequency adjusters) increase it by 100-150 percent. Overall, the lower the frequency of adjustments during times when economy is stable, the stronger the reaction to a shock to marginal cost.

Third, these observed differences in the frequency of price adjustments are strongly connected to the market elasticity of demand as well as the firms' elasticity of demand as measured by price markups (Jaimovich and Floetotto (2008), Feenstra and Weinstein (2010). Analysis shows that on the aggregate, firms adjust prices more frequently if they face lower market elasticity and lower firms elasticity of demand. Thus, the firms that lose the fewest customers as a result of price change adjust their prices more frequently.

On per-category level, this relationship holds for nondurable goods and services (associated with lower firms' elasticity of demand) and is reversed for the durables (associated with highest firms' elasticity of demand). This could be explained in the framework of industrial organization literature. Akerlof and Yellen (1985) and

Arbatskaya and Bayel (2004) argue that keeping prices stable is more costly for the firms operating in markets with higher level of competition. This finding suggests that there is a non-monotonicity: relationship between duration of prices and elasticity of demand change depending on the level of elasticity of demand the firm is facing.

Fourth, currently nominal rigidities are often modeled either using time-dependent pricing or state-dependent pricing. In time-dependent pricing approach (Calvo (1983)) frequency of price adjustments is exogenous and, thus, does not match the facts discussed above. The standard menu cost model representing state-dependent approach to modeling price rigidities (Sheshinski and Weiss (1977), Golosov and Lucas (2007), and Nakamura and Steinsson (2008b)) also cannot reproduce the facts stated above. A standard Dixit-Stiglitz aggregator assumes that one firm is producing one good and changes in price do not affect future demand. In this setting, the curvature of the profit function is defined by the elasticity of demand: a higher elasticity of demand is reflected in a higher frequency of price adjustments. This relationship does not change regardless of magnitude of the shock to the marginal cost.

I also examine the sizes of price adjustments between goods and across time. I find that percent changes in size of adjustment stay relatively stable across time and do not vary significantly among the goods.

Pricing decisions made by firms including the decision on whether or not to change the price at each point in time is a widely discussed topic. It is being examined in both theoretical and empirical literature.

A number of papers establish and examine facts about prices and different aspects of the frequency of price adjustments. Bils and Klenow (2004) establish the frequency of price changes for 350 categories of goods in the U.S. at approximately 4.3 months and find differences in the frequency among goods. Nakamura and Steinsson (2008b) further this discussion and find differences between the frequency of price increases and decreases as well as the covariance of price increases with inflation in the U.S.. Gagnon (2009) establishes that the frequency of price adjustments is connected to inflation at high levels of inflation. I combine analysis across time, across goods, and across different economic conditions and further explore the factors that can explain observed differences.

Another branch of literature examines the potential mechanisms behind price adjustments. Burstein, Eichenbaum, and Rebelo (2005a) and Burstein, Eichenbaum, and Rebelo (2005b) examine the role of tradable and non-tradable goods as well as non-tradable portion of tradable goods in movements of real exchange rates. Gopinath and Itskhoki (2010) discuss how primitives of the profit function define the frequency of price adjustments and examine the effects these have on incomplete exchange rate pass-through. A number of theoretical papers Rotemberg (2005); Chevalier and Scharfstein (1996) , Vincent and Kleshchelski (2009), Sim, Schoenle, Zakrajsek, and Gilchrist (2014) explain differences in pricing decisions across firms and between industries by differences in demand these firms are facing. Model developed by Vincent and Kleshchelski (2009) suggests non-monotonicity in relationship between pass-through and level of switching costs. This could be a potential explanation for the non-monotonicity in the Mexican data.

Industrial organization literature displays ambiguous findings on the relationship between the frequency of price adjustments and the market power. For example, Klemperer (1987) suggests that monopolies that compete for the same customer base could be worse off than oligopolies. On the contrary, Shy (2002) empirically shows that larger banks face higher switching costs and yet they charge higher prices. Fisher and Konieczny (1995) find that monopolistic newspapers prices are less rigid than oligopolistic newspapers, while Carlton (1986) finds a positive relationship between price rigidity and industry concentration for certain products used in manufacturing. In macro literature, Bils and Klenow (2004) find that goods sold in more concentrated markets (measured by the markups) adjust prices more frequently – a finding that, however, disappears when energy-related goods or fresh foods are controlled for.This paper empirically establishes connection between the market power of the firm and the frequency of price adjustments.

The frequency of price adjustments is also an important part of the mechanism generating price rigidities and as such is often used to examine various macroeconomic aspects as well as policy implications. A fourth branch of literature uses this factor for such analyses. It is adopted by different types of models – from time-dependent models like Calvo (1983), (Christiano, Eichenbaum, and Evans 2005), and Smets and Wouters (2007) to state-dependent models (Caplin and Spulber (1987), Dotsey, King, and Wolman (1999), Gertler and Leahy (2008), and Golosov and Lucas (2007)).

The paper proceeds as follows: Section I discusses the data. The facts about the frequency of price adjustments among goods and across time are established in Section II. Section III contains the conclusions on factors affecting the frequency of price adjustments. The match of the facts to the standard models is discussed in Section IV. Section V concludes.

II. Data

I use monthly pricing data on goods used for computation of CPI in Mexico from January 1994 to July 2002. The data covers period of time in the history of Mexico that includes significant devaluation of peso vis-a-vis U.S. dollar. By December of 1994 Mexican Tesobonos (dollar-indexed short-term government debt) was around 2 billions USD, international reserves were inadequate to support Mexico's obligations, the country had to move to floating exchange rate from a previously sustained fixed-exchange-rate system which led to significant devaluation of the peso and a collapse of the Tesobono market - investors chose not to roll over their holdings. The situation continued through beginning of 1995 when the Mexican government was on a verge of default. At this point U.S. government offered Mexico substantial financial aid (Braun, Mukherji, and Runkle (1996)). This economic situation was characterized a collapse in the peso by more than 40% in one week in December of 1994. This devaluation was accompanied by significant movements in inflation and real interest rates. In 1995 inflation reached 92% (Gagnon (2009)) and real interest rate from September 1994 to March 1995 changed by 43%. The data for inflation and exchange rates are shown in 1.

The data used in this paper is aggregated over 6.5 million price quotes collected by Banco de Mxico(Banxico). Details about composition of the data set can be found in Gagnon (2009).

Data is monthly and after adjustments for substitution of goods across the years the data contains over 230 goods. The goods are divided into 6 broad categories: Food and beverage; Housing; Apparel and Upkeep; Transportation; Medical Care;

Entertainment. Goods are also divided into nondurables, durables and services, as well as into regulated and non-regulated.

The frequency of price adjustments for each good in the sample is computed following Gagnon (2009).

III. Facts about frequency of price adjustments: data

I proceed to examine dynamics of the frequency of price adjustments in entire sample - from 1994 to 2002. This period covers both: the time of peso devaluation and the time when exchange rate in Mexico as well as inflation rate got back to stable state.

First, the size of price adjustments and frequency of price adjustments among different categories of goods were examined. Rapid changes in the overall price level, like the ones observed in Mexico, could happen through changes in the size of individual price adjustments or through change in frequency of such adjustments. As it is visible from the time-series of inflation Figure 1, inflation in Mexico was rapidly changing during the period under consideration. This exercise (results shown in Table 1 shows that there are in fact differences in frequency of price adjustments among different categories of goods: with nondurable goods being high-frequency adjusters changing prices with 0.33 probability in a month (corresponding to price duration of 3 months), durables adjusting prices every 5 months and services with price duration of around 8 months. There are no notable differences between the sizes of adjustments between these categories.

This motivates further examination of frequency. The analysis is establishing the fact that frequency of price adjustments is potentially an important economic phenomenon closely related to inflation dynamics. Differences in frequency with which firms change prices depending on a category of consumer good require further examination.

I also look at differences in duration of prices between different categories of goods and compare those to duration found in U.S. data from 1998 through 2009 by Klenow and Malin (2011) (Table 2). Price durations reported in the table are based on posted prices and include sales. It is clear that overall there are significant differences in duration of prices between categories, between countries, and between different periods in Mexican history. Price durations for nondurables and services as well as for food and medical care are higher in U.S. Durable goods and other categories of goods show duration that is higher in Mexico. It is also worth mentioning that rankings of the goods by durations differ between the two countries. Durable goods have lowest duration of prices in U.S., in Mexico the duration is lowest for non-durables. In a CPI classification household goods and transportation goods are the highest frequency adjusters in U.S.. In Mexico food and apparel categories are changing prices most often. This could be explained by differences in the structure of demand between the countries with different per-capita GDP and different shares of income spend by a household for different goods.

Also, for all categories of goods in Mexico, price durations during 1995 (a year associated with high inflation) for all categories of goods is significantly lower than in other years of the sample.

As a second step to examining facts about frequency of price adjustments, different categories of goods were examined across time. Monthly frequencies for each good over each year in the sample were aggregated, thus obtaining yearly values for every good.

Figure 2 shows evolution of the frequency over the years for the three broad goods categories. It is apparent that nondurable goods adjust prices more frequently than durable goods, which, in turn, adjust prices more often than services. Right after peso had devalued, the goods in all categories increase frequency of price changes. Thus devaluation of the currency significantly changes behavior of price setters regardless of the category. In the years following large currency devaluation the frequency is decreasing. Median duration of price adjustments for non-durable goods in 1995 is around 2 months, for durables is around 3.4 months, and for services is around 3.8 months. It is clear that frequency of price adjustments between durables and services gets very close in the year of high inflation. Later in the sample period, median duration of goods is around 3 months for nondurables, 5 months for durables and 6 onths for services.

Figure 3 depicts changes in price-setting behavior of the firms selling three broad categories of goods. As it is clearly visible, the reaction to 1994 peso devaluation is much stronger for services (low frequency adjusters) - the change is about 150 percent. Second strongest reaction is recorded for durables (around 110 percent), and the smallest reaction of about 80 percent is shown for nondurables (high frequency adjusters). This shows that on average slow adjusters have stronger reaction to a large shock than high frequency adjusters. This could be in-line with theories discussing variable markups and investments into the market share. In these theories firms often prefer to keep prices stable and absorb some costs in order to keep their market share, however, after a large enough shock, they pass everything onto the customers (Rotemberg (2005); Chevalier and Scharfstein (1996) , Vincent and Kleshchelski (2009), Sim, Schoenle, Zakrajsek, and Gilchrist (2014)).

The above exercise was repeated for the 6 categories of goods following Banxico CPI classification: Food and beverage; Household supplies; Apparel and Upkeep; Transportation; Medical Care; Entertainment. I compute median frequencies of price adjustments across goods in each category.

As it is reflected in Figure 4, highest adjusters among the categories are the Food category fluctuating around 0.3 and the Apparel category at around 0.25 through the sample, all other goods adjust prices less frequently ranging from 0.10 to 0.20. Thus, clearly, there are differences among these categories of goods which should be examined further. As in previous section, changes in frequency among six categories of goods are examined.

Following Figure 4 it is clear that frequency of price adjustments among all goods went up during 1995 following the exchange rate shock. However, ranking of the levels of price adjustments stay the same – Food and Apparel still adjust prices more frequently than all other goods increasing to around 0.50 and 0.40 respectively while frequencies of most other categories are around 0.30. In the following years frequency decreases for all categories of goods. However, Figure 5 depicting growth rates of the frequency of price adjustments for all categories indicates that reactions to the large devaluation of 1994 differs significantly among the categories. Food and Apparel, the goods that have very high levels of price adjustments, increase these levels by around 50% - much less than other categories like transportation and entertainment which increase the frequency by 100-150%. Thus again, there are some differences among these categories of goods that result in different reactions to the cost shock and require additional examination.

IV. Facts about frequency of price adjustments: relationships

Previous section describes differences in frequency of price adjustments between different categories of goods. In this section I look closer at reasons that may enplane such differences. I also map goods using Classification of individual consumption by purpose (COICOP) classifications into industries (Statistical classification of products by activity (CPA)) in order to explore price setting behavior of the firms selling these goods.

In literature, differences in frequency of price adjustment are sometimes attributed to such elements of profit function as own price elasticity of demand as in Gopinath and Itskhoki (2010). In the micro literature, elasticity of demand for the firm is proportional to the degree of competitiveness of the market as well as to own price elasticity of the good (market elasticity of demand) Pindyck (2013). For example, in a simple case of Cournot competition with firms of the same size

$$E_d = nE_D \tag{64}$$

Where E_d is elasticity of demand for the firm, n is number of firms and E_D is market elasticity of demand. It is straightforward to compute E_d for the market where firms sizes differ. Number of firms producing the good is inverse of Herfindahl-Hirschman index (HHI) for the market

$$HHI = \sum_{i=1}^{m} S_i^2$$

$$E_d = \frac{E_D}{HHI}$$

In addition, Lerners index measuring market power: $L = \frac{P-MC}{P} = \frac{-1}{E_d}$ where E_d is firm's elasticity of demand. The formula for Lerners index is also a definition of markup.

IV.1. Market elasticity of demand. In order to examine this connection, market elasticities of demand computed for different categories of goods by Seale, Jr., and Bernstein (2003) are used. These values are estimated from expenditure and consumption volume data for 114 countries including Mexico from the 1996 International Comparison Project (ICP) for nine broad categories of goods that correspond to the categories in Mexican CPI data. These categories are aggregated from product-level data. The data contains information on budget shares for each category of goods and own price elasticities are computed from estimated parameters of an aggregate demand system. Authors report three types of elasticities: Frisch elasticity (own price changes but marginal utility of income stays constant), Slutsky elasticity (changes in demand due to own price changes while holding real income constant), and Cournot elasticity (changes in demand due to own price changes while real income changes). Resulting numbers are reported in the Table 3. All three ways to compute elasticities produce the same rankings among categories of goods and in general are very close to each other numerically.

IV.2. Firms elasticity of demand. The second element I will use for my analysis is firm's elasticity of demand. As it has been mentioned above, this elasticity can be approximated by an inverse of price markups.

Markups for different industries were computed using OECD STAN Input-Output tables for Mexico. Markups are defined as Gross Operating Surplus divided by Gross Output (price minus cost over price) similar to Bloom, Blundell, Griffith, and Howitt (2005). Results are shown in the Table 4.

IV.3. Analysis of relationship between elasticities of demand and frequency of price adjustments. The Table 5 below summarizes differences in elasticities of market demand and firm's demand as well as in frequency of price adjustments between broad categories of goods. It is clear that market elasticity of demand is high for nondurables and services, while firm's elasticity of demand is highest for durables. This fact suggests different structure of demand for the three categories of goods.

Thus differences in price setting behavior of the firms could be explained by differences of demand they are facing. Overall elasticity of demand could be used as a proxy for measuring how price changes of the firms can change the size of the customer base. A number of theories attributes price stickiness and willingness of the firms to absorb cost shocks, (e.g.: exchange rate shock), to their care for customer base (Rotemberg (2005) and Vincent and Kleshchelski (2009))).

First, in order to understand the nature of relationship between market elasticity, firm's elasticity and frequency of price adjustments, I compute correlations between these three factors for different categories of goods. Results are presented in the Table 6.

Correlations computed for entire sample indicate negative relationship between frequency of price adjustments and both: market elasticity and firm's elasticity of demand. This suggests that firms exploit the market power they have - the less elastic is the demand, the more frequently the firm would adjust prices. This relationship, however, is much stronger for market elasticity of demand (correlation of -0.477)than for firm's elasticity of demand (correlation of -0.21). This suggests that overall, firm selling bread can change prices more often (and pass through any costs on the consumers), than firms selling caviar. It is also important to note that correlation between firms and market elasticity is not high.

However, once correlations are computed for three broad categories of goods, this negative relationship only holds for non-durables and services and is reversed for durables. It appears that for durable goods the more elastic is the demand, the more frequently firms adjust prices. A correlation coefficient between frequency and firms elasticity is still negative, however this coefficient is only significant at 68 percent. Also, correlation between market and firms elasticity for durable goods is low and also is only significant at 68 percent. Positive relationship between frequency and elasticities is in line with findings of the industrial organization literature: firms operating competitive markets have to adjust prices as soon as other firms adjust their prices (Carlton (1986)).

As a second step after computing correlations, I perform regression analysis. In the model where frequency of each good is θ_i, absolute value of market elasticity is

$|E_{D,i}|$ and absolute value of firms elasticity is $|E_{d,i}|$:

$$\theta_i = \alpha + \beta_1|E_{D,i}| + \beta_2|E_{d,i}| + u_i$$

Results of regression analysis are shown in Table 7. These results confirm findings of correlation analysis: for the sample of goods as a whole, higher market elasticity and firms elasticity of demand result in decreases in frequency of price adjustments. All coefficients are significant at 99 significance level, however, again, the coefficient for firm's elasticity of demand is low compared to the coefficient for the market elasticity. This relationship holds for nondurables and services, however, for the services coefficient for the market elasticity decreases compared to other goods. In addition, same as for correlations, higher frequency of price adjustments for the durables is associated with higher market elasticity of demand, but still has negative relationship with firm's elasticity of demand. These differences in behavior among firms could possibly be attributed to the overall level of firm's elasticity of demand: firms selling non-durable goods and services face less elastic demand (E_d is 3.30 and 2.77 respectively), while durables face a more elastic demand (E_d is 5.00). Again, this confirms that among firms operating in very concentrated markets, higher elasticity means more adjustments, while at the lower levels of market concentration this relationship can be opposite.

V. Model

This section demonstrates how standard models can not explain the facts discussed above. There are two major types of models that model price rigidities using frequency of price adjustments: time-dependent and state-dependent models.

V.1. Time-dependent models. First type of models assume that a fraction of firms can re-optimize its profit and change the price to the optimal one, while the remaining fraction of firms can not re-optimize (Calvo (1983)). A standard firms problem in this setting is as following.

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

$$Z_t L_t(i) = Y_t(i)$$

where $Y_t(i)$ is the production of good i.

The technology shock Z_t follows a unit root process with a growth rate $z_t \equiv \ln(Z_t/Z_{t-1})$ such that

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

where the distribution for ε_{zt} is normal$(0, \sigma_z^2)$. Following Calvo (1983), each firm sets prices according to a staggering mechanism. For each period, a fraction $\theta_{p,t}$ of firms cannot re-optimize its price optimally and indexes them according to the rule

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

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

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

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. In this setting, frequency of price adjustments is purely exogenous and non of the facts described above can be reconciled within this model.

V.2. Menu cost models. For this analysis partial equilibrium menu cost model similar to Sheshinski and Weiss (1977), Golosov and Lucas (2007), and Nakamura and Steinsson (2008) was used.

Each firm uses the following technology for production:

$$y_t(z) = A_t(z) L_t(z)$$

where production $y_t(z)$ at time t depends on productivity shock $A_t(z)$ and quantity of hired labor $L_t(z)$. Each firm faces demand:

$$c_t(z) = C \left(\frac{p_t(z)}{P_t} \right)^{-\theta}$$

where $P_t(z)$ is the price level at period t, C is the market demand for the good, $p_t(z)$ is the nominal price that firm charges for the good and $c_t(z)$ is demand for the firm's good. In order to simplify analysis following Nakamura and Steinsson (2008) I assume

$$\frac{W_t}{P_t} = \frac{\theta - 1}{\theta}$$

Where W_t is the wage level in economy. Combining above equations firm's profit function becomes:

$$\Pi_t = C\left(\frac{p_t(z)}{P_t}\right)^{-\theta}\left(\frac{p_t(z)}{P_t} - \frac{\theta-1}{\theta}\frac{1}{A_t(z)}\right)$$

Firm would choose to adjust the price in the presence of some menu cost only in the case when the profit received from adjustment $\Pi(a)$ exceeds profit from non-adjustment $\Pi(p_0|a)$ by more than the menu cost.

$$L(a) = \Pi(a) - \Pi(p_0|a) > k$$

where k is some menu cost. Frequency of price adjustment thus is defined as

$$\Psi = PrL(a) > k$$

I assume $k = W_t K I_t(z)$ - if the firm decides to adjust it's price it would have to hire additional workers. Productivity $A_t(z)$ is assumed to follow AR(1) process:

$$log(A_t(z)) = \rho log(A_{t-1}(z)) + \varepsilon_t(z)$$

Also, assume that level of prices P_t follows

$$log(P_t) = \mu_p + log(P_{t-1}) + \nu_t$$

First,comparison between different values of elasticity of demand θ on frequency of price adjustments is conducted using one period profit function. This illustrates how curvature of the profit function is defined by benchmark elasticity of demand. The model is calibrated to US data, however for the exercise at hand these values are acceptable. This exercise demonstrates how elasticity of demand affects the curvature of the profit function. Figure **??** shows two profit function - in blue for elasticity of demand equaling 7, red one for elasticity of demand equaling 3. These values are within the ranges used in the literature for similar models (Nakamura and Steinsson (2008b). It is logical that higher elasticity of demand results in overall lower levels of profit. Dotted lines of corresponding colors represent profit functions shifted down as a result of negative shock to marginal cost. Label Max_1 represents the point at which firms were maximizing their profits in a no shock environment. In case if after the shocks firms would not be willing to adjust their prices and move to a new maximum point labeled as Max_2 they would lose the corresponding increase in profit. From this simple numerical example it is clear that firms facing higher elasticity of demand would forgo larger increase in profit (0.076) than firms with lower elasticity of demand (0.032). Thus firms facing less elastic demand are less likely to adjust their prices irrespective of the size of the menu cost. Figure 7 confirms that this relationship holds for every value of elasticity: higher elasticity of demand is associated with higher increase in profit from adjustment. Thus higher elasticity of demand always results in higher probability of adjusting the price. This Figure also indicates that increase in the shock results in higher differences among firms facing different demand. Size of the shock increases frequency of price adjustments for the firms with higher elasticity by more than for the firm facing less elastic demand.

This analysis shows that standard menu cost models can not reproduce the facts found in the data. The relationship between frequency of price adjustments and elasticity of demand is positive. In the data, this corresponds only to behavior of the firms selling durable goods, which, on average, face very high elasticity of firm's demand and thus operating in the very concentrated markets.

In addition, increase in frequency of price adjustments after a larger shock to marginal cost is higher for high frequency adjusters than for lower frequency adjustments which contradicts the data facts.

VI. Conclusion

This paper establishes a number of facts regarding frequency of price adjustments using disaggregated data from Mexico 1994-2002. Since this data covers period of time that includes large peso devaluation in December of 1994, it provides valuable insights into price-setting mechanism of firms in different economic circumstances. The data suggests that there are differences in frequency of price adjustments between times of relatively stable economic conditions and times of instability - on average all goods start to adjust prices more after a large cost shock.

There are also differences between frequency of price adjustments between non-durables, durables and services, with the latter adjusting prices less frequently throughout the sample. Differences also exist between six different categories of goods adopted from the Mexican CPI classification with food and apparel adjusting prices most frequently. Comparison between duration of prices for various categories in Mexico and USA also revealed differences in both: frequency and rankings of the goods by the duration.

Following large devaluation, low frequency adjusters show a stronger reaction than high frequency adjusters.

The results of analysis suggest that firms facing higher market elasticity of demand are adjusting prices less frequently than those with lower elasticity consistently throughout the sample. Same relationship is true for firms elasticity of demand as measured by markups. When similar analysis is done for the goods in different categories, the relationship holds for durables and services and is reversed for durable goods.

These facts can not be reconciled with a standard benchmark menu cost model. In benchmark setting frequency of price adjustments is positively related to elasticity of demand.

2.A. Tables

	Frequency			Percent change in price		
	25%	Median	75%	25%	Median	75%
All goods	0.16	0.26	0.45	-0.00	0.01	0.02
Non-Durable (60%)	0.22	0.33	0.63	-0.00	0.01	0.02
Durable (5%)	0.13	0.20	0.29	0.00	0.01	0.02
Services (17%)	0.12	0.17	0.24	0.00	0.01	0.02

Table 1. Frequency of price adjustments and percent change in price for the different categories of goods

Classification	Median duration (USA) Klenow and Malin (2011)	Median duration (Mexico)		
		Entire sample	1995	Not including 1995
Non-durable goods	3.4	2.9	2.14	3.10
Durable goods	1.8	4.8	3.44	5.00
Services	7.6	5.7	3.82	5.93
Food	3.4	2.5	1.89	2.66
Household goods	1.9	5.2	3.61	5.46
Apparel	2.8	3.7	2.67	3.88
Transportation	1.8	7.1	4.10	7.47
Medical Care	10.0	5.2	3.62	5.38
Recreation	6.3	6.3	3.97	6.54

Table 2. Durations of prices in Mexico and USA

	Elasticity		
Product	Frisch	Cournot	Slutsky
Food and beverage	-0.479	-0.581	-0.385
Housing	-0.96	-0.963	-0.890
Apparel and Upkeep	-0.739	-0.755	-0.694
Transportation	-0.972	-0.975	-0.849
Medical Care	-1.072	-1.065	-0.967
Entertainment	-1.147	-1.137	-1.069

Table 3. Own-price elasticities of demand (Seale, Regmi, and Bernstein (2003))

Code	Sector	Markups
C01T05	Agriculture, hunting, forestry and fishing	0.51
C15T16	Food products, beverages and tobacco	0.30
C17T19	Textiles, textile products, leather and footwear	0.19
C20	Wood and products of wood and cork	0.28
C21T22	Pulp, paper, paper products, printing and publishing	0.21
C23	Coke, refined petroleum products and nuclear fuel	0.10
C24	Chemicals and chemical products	0.21
C25	Rubber and plastics products	0.17
C26	Other non-metallic mineral products	0.38
C27	Basic metals	0.27
C28	Fabricated metal products except machinery and equipment	0.19
C29	Machinery and equipment n.e.c	0.10
C30	Office, accounting and computing machinery	0.09
C31	Electrical machinery and apparatus n.e.c	0.14
C34	Motor vehicles, trailers and semi-trailers	0.20
C36T37	Manufacturing n.e.c; recycling	0.20
C40T41	Electricity, gas and water supply	0.24
C50T52	Wholesale and retail trade; repairs	0.55
C55	Hotels and restaurants	0.52
C60T63	Transport and storage	0.41
C70	Real estate activities	0.88
C71	Renting of machinery and equipment	0.81
C72	Computer and related activities	0.17
C80	Education	0.21
C85	Health and social work	0.32

TABLE 4. Markups: Gross Operating Surplus divided by Gross Output

	Medians		
	Nondurables	Durables	Services
E_D	0.48	0.96	0.97
E_d	3.30	5.00	2.77
Frequency	0.33	0.20	0.17

TABLE 5. Market elasticity of demand, firms elasticity of demand and frequencies for different categories of goods

Entire sample			
	Frequency	Market Elasticity	Firms Elasticity
Frequency	1		
Market Elasticity	-0.4729^{***}	1	
Firms Elasticity	-0.2105^{***}	-0.3589^{***}	1
Nondurables			
Frequency	1		
Market Elasticity	-0.3500^{***}	1	
Firms Elasticity	-0.3486^{***}	0.8603^{***}	1
Durables			
Frequency	1		
Market Elasticity	0.3340^{***}	1	
Firms Elasticity	-0.0720^{*}	-0.0330^{*}	1
Services			
Frequency	1		
Market Elasticity	-0.1337^{***}	1	
Firms Elasticity	-0.1069^{***}	0.1533^{***}	1

TABLE 6. Correlations between frequency of price adjustments, market elasticity of demand, and firms elasticity of demand.

Category of goods	Market Elasticity	Firms Elasticity	Intercept
All	$-.46^{***}$	$-.007^{***}$	$.67^{***}$
	0.006	0.001	0.005
Nondurable	$-.43^{**}$	$-.019^{***}$	$.69^{***}$
	0.02	0.008	0.02
Durable	$.79^{***}$	$-.007^{***}$	$-.51^{***}$
	0.07	0.003	0.07
Services	$-.091^{***}$	$-.004^{**}$	$.18^{***}$
	0.014	0.003	0.015

TABLE 7. Regression results

2.B. Figures

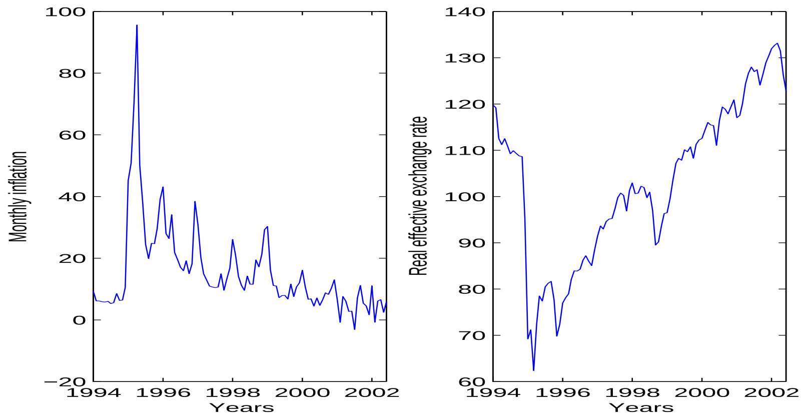

FIGURE 1. Left sub-plot represents monthly inflation in Mexico in 1994-2002, right sub-plot shows real effective exchange rate in 1994-2002: both data series are retreived from the federal Reserve Bank of St. Louis FRED database

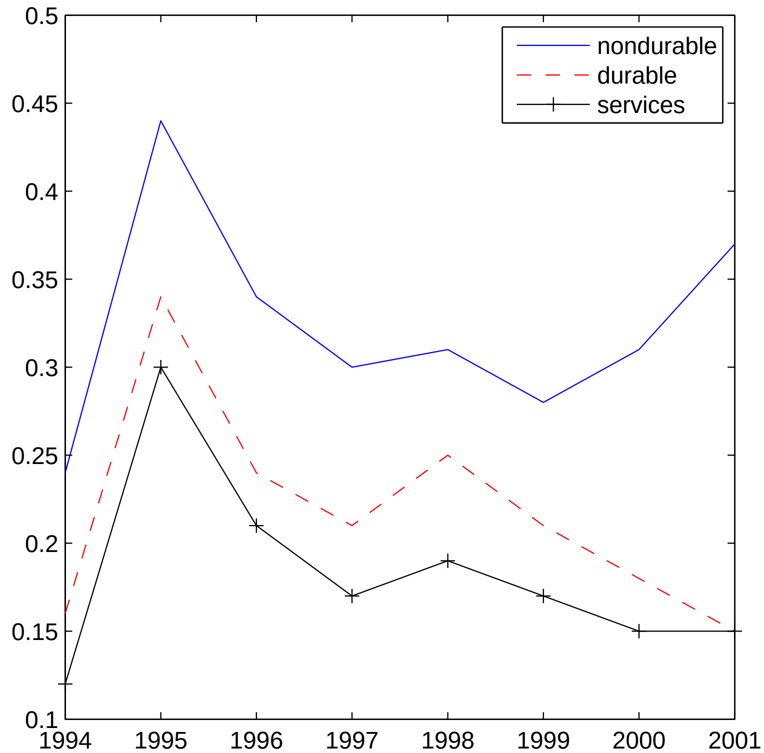

FIGURE 2. Frequncy of price adjustments is reflected on y-axis. Blue solid line is median values of the frequency of price adjustments of the nondurables, red dotted line plots median values of the frequency of price adjustments of the durables, black like with crosses plots median values of the frequency of price adjustments of the services respectively

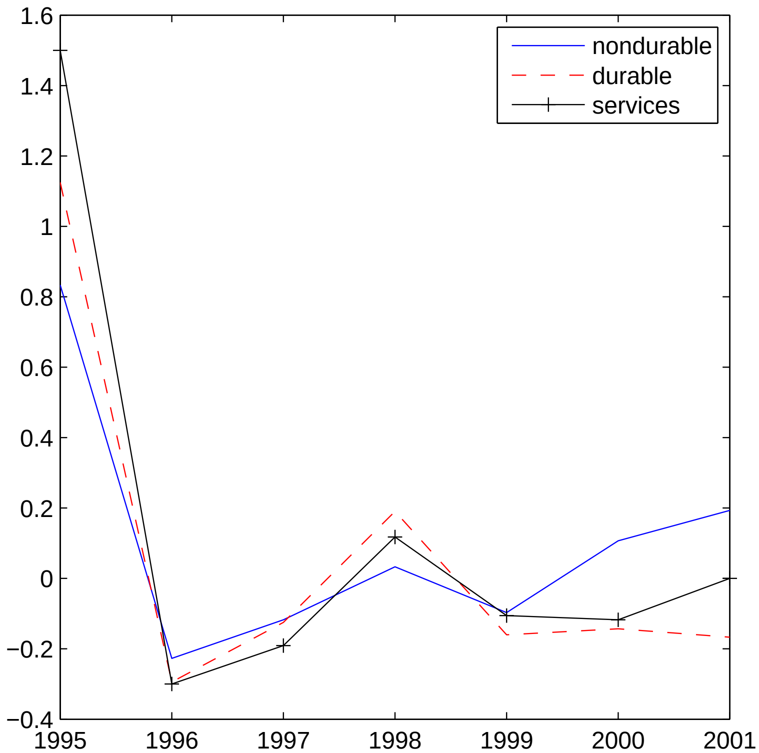

FIGURE 3. Percent change in frequncy of price adjustments is reflected on y-axis. Blue solid line is median values of the percent change in frequency of price adjustments of the nondurables, red dotted line plots percent change in frequency of price adjustments of the durables, black like with crosses plotspercent change in frequency of price adjustments of the services respectively

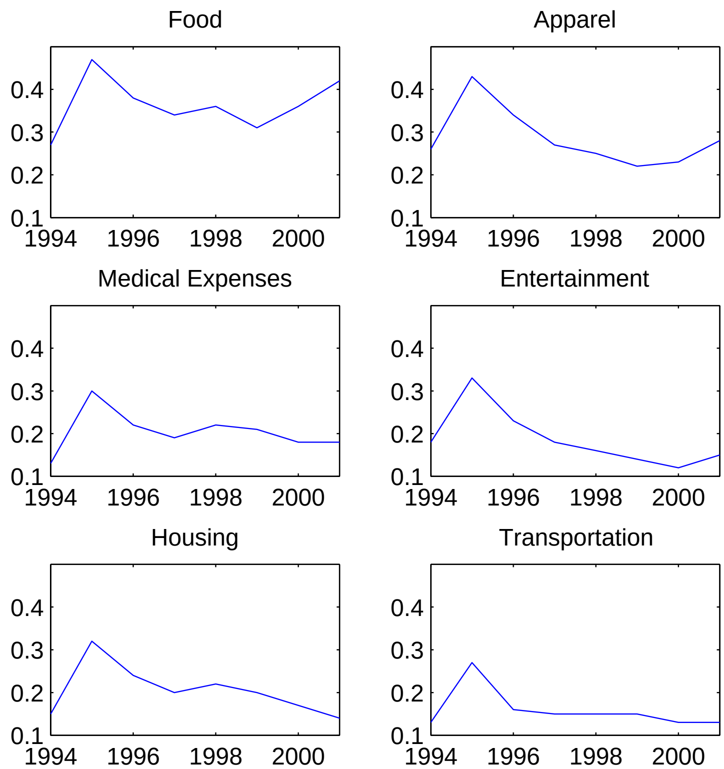

FIGURE 4. Each sub-plot shows frequency of price adjustments for different categories of goods from 1994 to 2001

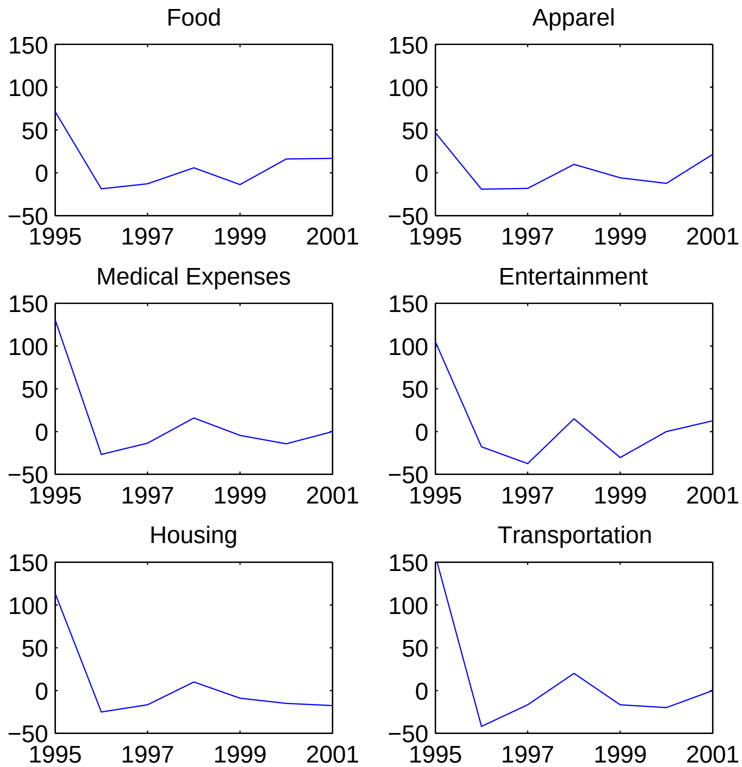

FIGURE 5. Each sub-plot shows percent change in frequency of price adjustments from year to year for different categories of goods from 1994 to 2001

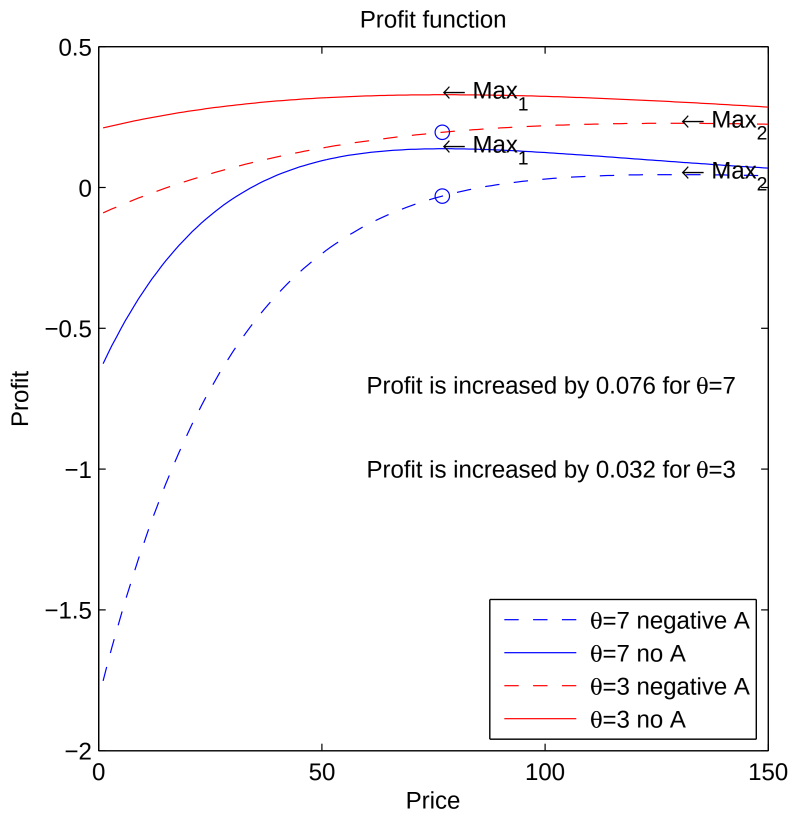

FIGURE 6. Solid lines on the plot represent profit function of the firm with no shock to marginal cost. Dotted lines represent shifts of the profit functions after one standard deviation shock to the marginal cost. Red lines are for $\theta = 3$, blue lines are for $\theta = 7$

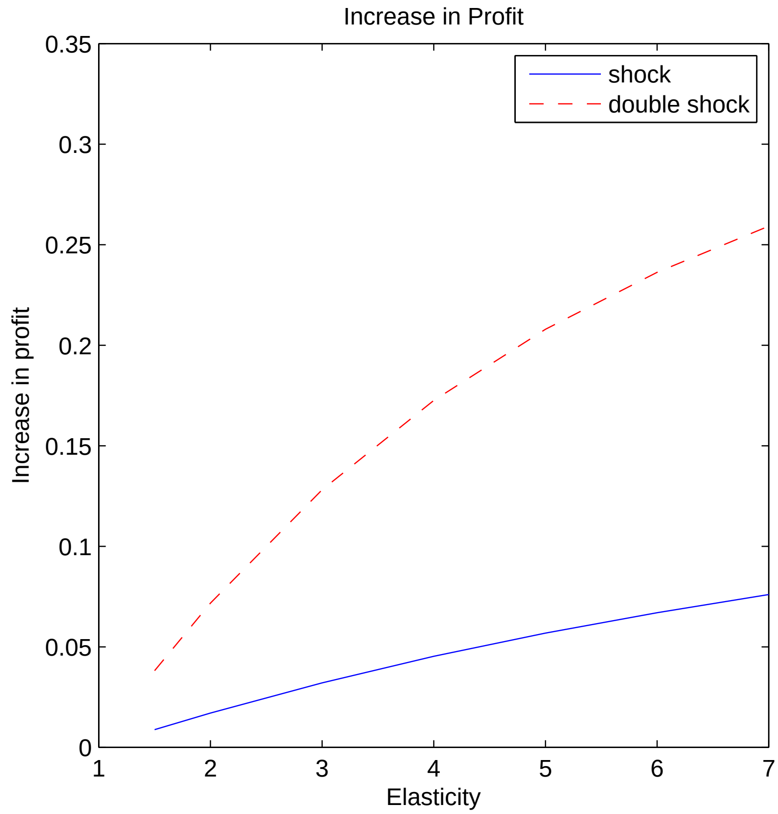

FIGURE 7. Solid blue line represents increases in profit from adjustment of prices after a shock associated with different values of elasticities of demand, red blue line shows increases in profit after two standard deviations shock

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