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Real and Nominal Rigidities in Price Setting: A Bayesian Analysis Using Aggregate Data

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Abstract

This paper uses the Bayesian approach to solve and estimate a New Keynesian model augmented by a generalized Phillips curve, in which the shape of the price reset hazards can be identified using aggregate data. My empirical result shows that a constant hazard function is easily rejected by the data. The empirical hazard function for post-1983 periods in the U.S. is consistent with micro evidence obtained using data from similar periods. The hazard for pre-1983 periods, however, exhibits a remarkable increasing pattern, implying that pricing decisions are characterized by both time- and state-dependent aspects. Additionally, real rigidity plays an important role, but not as big a role as found in empirical studies using limited information methods.

JEL classification: E12; E31

Key words: Real rigidity, Nominal rigidity, Hazard function, Bayesian estimation

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1 Introduction

Since the early 90's the New Keynesian paradigm has been widely used in the applied monetary analysis. As a result, interest in the empirical investigation of price rigidity has been rekindled: understanding how and to what extent prices adjust to changes in market conditions is fundamentally important in explaining short-run inflation dynamics and non-neutrality of monetary policy.

This paper is broadly related to progress in developing empirical models of sticky prices based on the New Keynesian framework. The early empirical model of sticky prices was solely based on the New Keynesian Phillips curve (hereafter: NKPC) under the Calvo pricing assumption (See, e.g. Gali and Gertler, 1999, Gali et al., 2001 and Sbordone, 2002). These authors estimated the NKPC with GMM, and found a considerable degree of price rigidity for both the U.S. and Europe. The empirical price reset hazard rate is around 20% per quarter for the U.S. and 10% for Europe. These results, however, are at odds with increasingly available micro evidence in two ways. First, recent micro studies generally conclude that the average frequency of price adjustments at the firm's level is not only higher, but also differs substantially across sectors in the economy¹. Second, the Calvo assumption implies a constant hazard function, meaning that the probability of adjusting prices is independent of the length of the time since the last price revision, and the flat hazard function has been largely rejected by empirical evidence from micro level data (See, e.g.: Cecchetti, 1986, Campbell and Eden, 2005 and Nakamura and Steinsson, 2008a). Given these discrepancies between the macro and micro evidence, empirical models allowing for more flexible price durations or hazard functions have become more popular in the recent literature. Jadresic (1999) presented a staggered pricing model featuring a flexible distribution over price durations and used simple OLS estimation to demonstrate that the dynamic behavior of aggregate data on inflation and other macroeconomic variables provide information about the disaggregated price dynamics underlying the data. More recently, Sheedy (2007) constructed a generalized Calvo model and parameterized the hazard function in such a way that the resulting NKPC implied intrinsic inflation persistence when the hazard function was upward sloping. Based on this hazard function specification, he estimated the NKPC using GMM and found evidence of an upward-sloping hazard function. Coenen et al. (2007) developed a staggered nominal contracts model with both random and fixed durations, and estimated the generalized NKPC with an indirect inference method. Their results showed that price rigidity is characterized by a very high degree of real rigidity, as opposed to modest nominal rigidity with an average duration of about 2-3 quarters. Carvalho and Dam (2008) estimated a semi-structural multi-price-duration model with the Bayesian approach, and found that allowing for prices to last longer than 4 quarters is crucial to avoid underestimating the relative importance of nominal rigidity. Their estimates, however, also imply a substantial degree of real rigidity compared to the level deemed plausible in the macro literature (See: e.g. Woodford, 2003).

In this paper, I revisit these issues regarding real and nominal price rigidities by estimating a fully-specified DSGE model with the full information Bayesian approach. In the theoretical part of this paper, I construct a DSGE model featuring nominal rigidity that allows for a flexible hazard function of price setting and real rigidity following Basu (1995). I derive the generalized

¹See: e.g. Bils and Klenow (2004), Alvarez et al. (2006) Midrigan (2007) and Nakamura and Steinsson (2008a) among others.

NKPC, which incorporates components such as lagged inflation, future and lagged expectations of inflation and real marginal costs. This version of the Phillips curve nests the Calvo case in the sense that, under a constant hazard function, effects of lagged inflation exactly cancel those of lagged expectations, so that, as in the Calvo NKPC, only current real marginal cost and expected future inflation remains in the expression. In the general case, however, both lagged inflation and lagged inflation expectations should be presented in the Phillips curve. Thanks to this richer dynamic structure, the resulting NKPC provides a new analytical apparatus which is capable to explore both forward- and backward-looking features of aggregate data, such as inflation.

Based on this generalized New Keynesian framework, my empirical analysis focuses on two aspects of price rigidity that are directly related to the estimates of the structural parameters. First, I am interested in the magnitude and especially the shape of the price reset hazard function, as microeconomic studies so far deliver conflicting evidence². The reason the micro data fails to reach a consensus is that, first, those data sets differ substantially in the range of goods included, the countries and time periods covered, and thereby make it difficult to compare results; and second, even though comprehensive micro data sets have now become available, they are usually short compared to the aggregate time series. Most of the CPI or PPI data sets for the U.S. or Europe are only available from the late 80's³. It is likely that the shape of hazard functions depends on the underlying economic conditions, and is therefore changing over the time periods of the collected data. As a result, conclusions drawn from a short data set are not necessarily valid for other periods. It is therefore desirable to explore the empirical shape of the hazard function by examining the long and consistent time series data as a complement to micro studies. My empirical results show that, for the subsample from 1983 to 2008, the estimated hazard function largely resembles that found in the microeconomic studies using data from similar periods. The hazard function is decreasing in the first two quarters and then largely flat, with spikes at the 4th and 6th quarters after the first adjustment. The estimated hazard function for periods before 1983 shows a similar pattern, but exhibits a remarkable increasing trend after the 4th quarter. One interpretation of this finding is that price setting is characterized by both time- and state-dependent aspects, but, in a turbulent economic environment, the state-dependent pricing plays a larger role in price decisions of the sticky sectors. The reason that my generalized time-dependent model is capable to capture the state-dependent pricing behavior in the data is the following: even though this framework literally has no state-dependent feature, meaning that the hazard function does not change over time by construction. In practice, however, one can apply it to data sets from different periods, in that hazards do change in subsamples. Therefore, this framework is flexible enough to empirically capture the state-dependent feature in the data, even though theoretically it is not.

Second, I study the magnitude of real rigidity implied by the estimates of the structural parameters in the model. As discussed above, models using limited information methods tend to find a high degree of real rigidity, even when allowing for a longer maximum price duration. Coenen et al. (2007) limited the maximum contract duration to 4 quarters in their model, and

²The results of those work on the empirical hazard function is not conclusive. Some find strong support for increasing hazard functions (e.g.: Fougere et al., 2005 and Sheedy, 2007), while others find evidence in favour of decreasing hazards (e.g.: Campbell and Eden, 2005, Alvarez, 2007 and Nakamura and Steinsson, 2008a).

³For more details see Table 2 in Alvarez (2007)

obtained a very high degree of real rigidity (0.004 for the U.S.)—defined as the sensitivity of new price contracts to aggregate real marginal cost, while Carvalho and Dam (2008) allowed for a longer price duration up to 8 quarters and, as a result, their estimate of real rigidity was improved by a factor of 10. However, as discussed in Woodford (2003), a value of real rigidity should be around 0.15 under plausible assumptions. I revisit this issue by using the Bayesian method with a full-fledged DSGE model. The full information Bayesian method has some appealing features in comparison to other methods employed in the literature. As pointed out by An and Schorfheide (2007), this method is system-based, meaning that it fits the DSGE model to a vector of aggregate time series. Through a full characterization of the data generating process, it provides a formal framework for evaluating misspecified models on the basis of the data density. In addition, the Bayesian approach also provides a consistent method for dealing with rational expectations – one of the central elements in most DSGE models. My empirical findings confirm the conclusions drawn by Carvalho and Dam (2008) that over restrictive truncation of the maximum duration tends to overestimate real rigidity at the expense of nominal rigidity. I find that the estimated real rigidity is decreasing, while the implied average duration of prices is increasing significantly with a rise in the maximum duration. Last but not least, I find that full information method improves the estimation result of real rigidity. The level of real rigidity obtained in this paper is broadly in line with the plausible values of strategic complementarity in pricing decisions.

Recently, identifiability becomes an important issue in the Bayesian DSGE literature (See: e.g. Canova and Sala, 2009 and Rios-Rull et al., 2009). In general, it is difficult to make sure that an identification delivers sensible inference, because the mapping between reduced-form coefficients and the structural parameters is commonly subject to a highly inscrutable nonlinear function based on theoretical assumptions in the model. A good identification requires that those theoretical assumptions, on which the mapping is based, should be robust or, at least, not seriously misspecified. In this paper, I am interested in identifying structural parameters regarding real and nominal rigidities from coefficients in the dynamic structure of the generalized NKPC. The mapping between the hazard function and reduced form coefficients is robust, because the underlying assumption of the general form hazard function does not depend on any particular pricing assumptions. In effect, it nests a wide range of pricing assumptions in the literature as limiting cases. On the other hand, estimated real rigidity depends on several structural parameters, some of which suffer from the under-identification problem (defined in Canova and Sala, 2009). In those cases, I conduct various sensitivity analyses to check robustness of my results.

The remainder of the paper is organized as follows: in section 2, I present the model with generalized time-dependent pricing and derive the New Keynesian Phillips curve; section 3 introduces the empirical method and the data I use to estimate the model, where the results regarding real and nominal rigidities are then presented and discussed; section 4 contains some concluding remarks.

2 A Sticky Price DSGE Model

In this section, I present a DSGE model of sticky prices due to both nominal and real rigidities. I introduce nominal rigidity by means of a general form of hazard functions⁴. A hazard function of price setting is defined as the probabilities of price adjustment conditional on the spell of time elapsed since the last price change. In this model, the hazard function is a discrete function taking values between zero and one on its time domain. Many well known models of price setting in the literature can be shown to imply hazard functions of one form or another. For example, the most prominent pricing assumption of Calvo (1983) implies a constant hazard function over the infinite horizon. On the other hand, real rigidity is introduced similarly as in Basu (1995), who emphasizes the intermediate input as a source of strategic complementarity in price decisions.

2.1 Representative Household

A representative, infinitely-lived household derives utility from the composite consumption good C_t , and its labor supply L_t , and it maximizes a discounted sum of utility of the form:

$$\max_{\{C_t, L_t, B_t\}} E_0 \left[\sum_{t=0}^{\infty} \beta^t \left(\frac{C_t^{1-\delta}}{1-\delta} - \chi_H \frac{L_t^{1+\phi}}{1+\phi} \right) \right].$$

Here C_t denotes an index of the household's consumption of each of the individual goods, $C_t(i)$, following a constant-elasticity-of-substitution aggregator (Dixit and Stiglitz, 1977).

$$C_t \equiv \left[\int_0^1 C_t(i)^{\frac{\eta-1}{\eta}} di \right]^{\frac{\eta}{\eta-1}}, \quad (1)$$

where $\eta > 1$, and it follows that the corresponding cost-minimizing demand for $C_t(i)$ and the welfare-based price index, P_t , are given by

$$C_t(i) = \left(\frac{P_t(i)}{P_t} \right)^{-\eta} C_t \quad (2)$$

$$P_t = \left[\int_0^1 P_t(i)^{1-\eta} di \right]^{\frac{1}{1-\eta}}. \quad (3)$$

For simplicity, I assume that households supply homogeneous labor units (L_t) in an economy-wide competitive labor market⁵.

The flow budget constraint of the household at the beginning of period t is

$$P_t C_t + \frac{B_t}{R_t} \leq W_t L_t + B_{t-1} + \int_0^1 \pi_t(i) di. \quad (4)$$

⁴In the theoretical literature, the general time-dependent pricing model has been first outlined in Wolman (1999), who studied some simple examples and found that inflation dynamics are sensitive to different pricing rules. Similar models have also been studied by Mash (2004) and Yao (2009).

⁵Even though it is arguable that assuming differentiated labor inputs is more realistic and theoretically desirable (see discussion in Woodford, 2003, Ch.3), my choice of uniform labor input can be justified by the following reasons: first, the homogeneous labor unit abstracts from the microfoundation that household packs different labor types in a fixed proportion in a labor supply unit and sale it in the competitive labor market. Second, I will introduce strategic complementarity through assuming intermediate inputs in the production function.

Where B_t is a one-period nominal bond and R_t denotes the gross nominal return on the bond. $\pi_t(i)$ represents the nominal profits of a firm that sells good i . I assume that each household owns an equal share of all firms. Finally this sequence of period budget constraints is supplemented with a transversality condition of the form $\lim_{T \rightarrow \infty} E_t \left[\frac{B_T}{\prod_{s=1}^T R_s} \right] \geq 0$.

The solution to the household's optimization problem can be expressed in two first order necessary conditions. First, optimal labor supply is related to the real wage:

$$\chi_H L_t^\phi C_t^\delta = \frac{W_t}{P_t}. \quad (5)$$

Second, the Euler equation gives the relationship between the optimal consumption path and asset prices:

$$1 = \beta E_t \left[\left(\frac{C_t}{C_{t+1}} \right)^\delta \frac{R_t P_t}{P_{t+1}} \right]. \quad (6)$$

2.2 Firms in the Economy

2.2.1 Production Technology

The production side of the economy is composed of a continuum of monopolistic competitive firms, each producing one variety of product i by using labor and all other intermediate products as inputs⁶. Each firm maximizes real profits, subject to the production function

$$Y_t(i) = Z_t L_t(i)^{1-a} M_t(i)^a, \quad (7)$$

where Z_t denotes an aggregate productivity shock. Log deviations of the shock, \hat{z}_t , follow an exogenous AR(1) process $\hat{z}_t = \rho_z \hat{z}_{t-1} + \varepsilon_{z,t}$, and $\varepsilon_{z,t}$ is white noise with $\rho_z \in [0, 1)$. $L_t(i)$ is the demand of labor by firm i and $M_t(i)$ is a composite intermediate input demanded by firm i , which is defined as follows:

$$M_t(i) \equiv \left[\int_0^1 M_t(i, k)^{\frac{\eta-1}{\eta}} dk \right]^{\frac{\eta}{\eta-1}}. \quad (8)$$

In equation (8), I assume that the composite intermediate input is aggregated in the same way as consumption goods. Given these assumptions, the cost minimization yields optimal demands for the k th intermediate input from firm i :

$$M_t(i, k) = M_t(i) \left(\frac{P_t(k)}{P_t} \right)^{-\eta}. \quad (9)$$

I assume that, in the economy, all intermediate products, $Y_t(i)$, can serve either as intermediate consumption goods or as inputs for the production of other intermediate products, and is given as

⁶The intermediate-input assumption is motivated by Basu (1995), who shows that introducing intermediate inputs is an important source of strategic complementarity in price setting. For earlier work, see Blanchard (1982). Most recently, Nakamura and Steinsson (2008b) show that real rigidity introduced by this assumption fits better to the micro evidence of price adjustments.

$$Y_t(i) = C_t(i) + \int_0^1 M_t(k, i) dk. \quad (10)$$

Substituting intermediate consumption and intermediate inputs by the demand functions in equations (2) and (9), I obtain the demand for intermediate good i :

$$Y_t(i) = \left(\frac{P_t(i)}{P_t} \right)^{-\eta} Y_t, \quad (11)$$

where $Y_t \equiv C_t + \int_0^1 M_t(i) di$. Note that in this economy, Y_t should be interpreted as gross output, while C_t represents the "value-added" output.

2.2.2 Pricing Decisions under Real Rigidity

Under assumptions of the firms' side of the economy, each firm determines profit-maximizing nominal price $P_t^*(i)$, given real marginal cost and the market demand for their goods (11)

$$\max_{P_t(i)} \Pi_t(i) = Y_t(i) \left(\frac{P_t(i)}{P_t} - mc_t \right).$$

It can be shown that, in a symmetric general equilibrium, real marginal cost (mc_t) equals⁷:

$$mc_t = \frac{(1-a)^{a-1}}{a^a} \left(\chi_H L_t^\phi C_t^\delta \right)^{1-a} \frac{1}{Z_t}. \quad (12)$$

Note that even though firms in the economy produce different goods using different inputs, firms' marginal costs are the same due to the symmetric input-output structure in the economy.

The first order condition for $P_t^*(i)$ yields the following optimally pricing equation:

$$\frac{P_t^*}{P_t} = \frac{\eta}{\eta - 1} mc_t. \quad (13)$$

Without nominal rigidity, the firm's price decision reduces to a simple period-by-period rule which sets the optimal price proportional to the real marginal cost by a fixed markup. Because real marginal cost is dependent only on aggregate variables, new prices should be common across all resetting firms.

To show how intermediate inputs give rise to real rigidity in this model, I log-linearize equation (13), along with the marginal cost equation (12) and the production function (7) around the deterministic steady state. Up to a log linear approximation, one can show that the log deviation of the relative price from the steady state ($\widehat{r\hat{p}}_t$) can be expressed as follows:

$$\begin{aligned} \widehat{r\hat{p}}_t &= \widehat{m\hat{c}}_t = \gamma (\kappa_1 \hat{c}_t - \kappa_2 \hat{z}_t) \\ \text{where } : \\ \gamma &= \frac{\eta(1-a) + a}{\eta(1-a) + a(1+\phi)} \\ \kappa_1 &= (\delta + \phi)(1-a) \\ \kappa_2 &= 1 + \phi. \end{aligned} \quad (14)$$

⁷The derivation is in Appendix (A).

In equation (14), parameters γ and κ_1 can be regarded as measures of real rigidity. The elasticity of relative prices to a change in real marginal cost is given by γ , while κ_1 measures the sensitivity of real marginal cost to the change in the output gap. Following Woodford (2003), price-setting decisions are called strategic complementarity when $\gamma\kappa_1 < 1$. When we assume that the monetary authority controls the growth rate of the nominal aggregate demand, \hat{m}_t , then the equilibrium dictates that $\hat{c}_t = \hat{m}_t - \hat{p}_t$. In this case, price adjustments are “sticky” even under a flexible price setting, because relative price reacts less than one-to-one to the monetary policy shock. On the other hand, price setting decisions can be called strategic substitutes when $\gamma\kappa_1 > 1$, so that relative price reacts strongly to monetary policy shocks. Finally the boundary case where $\gamma\kappa_1 = 1$ can be called strategic neutrality.

Now we can discuss how changes in the intermediate inputs share, a , affect the magnitude of real rigidity of price setting in the model. When setting a equal to zero, creating a linear production technology, then $\gamma = 1$ and $\kappa_1 = \delta + \phi$. Under the commonly used calibration values in the DSGE literature ($\delta = 1$, $\phi = 1$ and $\eta = 10$), the real rigidity parameter $\gamma\kappa_1$ is equal to 2 and price decisions are strategic substitutes. When the value of a rises, the real rigidity parameter becomes smaller, and price decisions become strategic complements to each other.

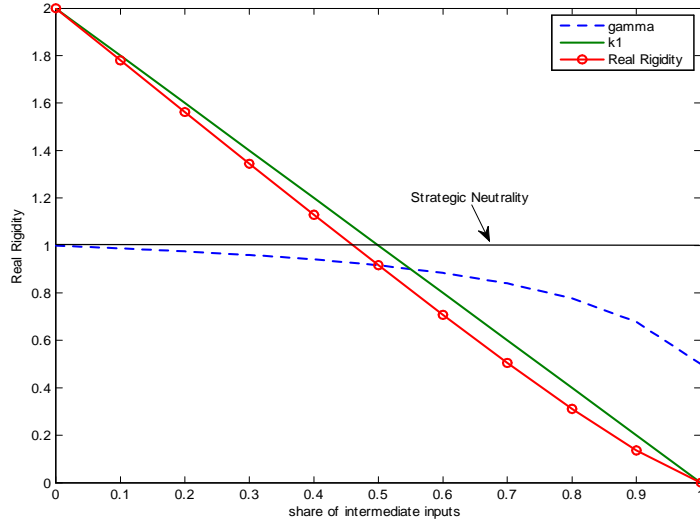


Figure 1: Real Rigidity When $\delta = 1$, $\phi = 1$ and $\eta = 10$

In figure (1), I plot values of γ and κ_1 against values of a , while setting $\delta = 1$, $\phi = 1$ and $\eta = 10$. In this special case, the elasticity of the relative price to a change in marginal cost, γ , is not sensitive to the input share, while κ_1 decreases linearly as a becomes larger. This means that, given the parameter values, real rigidity is mainly driven by the sensitivity of real marginal cost to changes in the output gap, and the degree of real rigidity is decreasing in a . With a modest level of the intermediate input share (around 0.5), real rigidity drops below the strategic neutrality threshold.

2.3 Pricing Decisions under Nominal Rigidity

In this section, I introduce a general form of nominal rigidity, which is characterized by a set of hazard rates depending on the spell of the time since last price adjustment. I assume that monopolistic competitive firms cannot adjust their price whenever they want. Instead, opportunities for re-optimizing prices are dictated by the hazard rates, h_j , where j denotes the time-since-last-adjustment and $j \in \{0, J\}$. J is the maximum number of periods in which a firm's price can be fixed.

2.3.1 Dynamics of the Price-duration Distribution

In the economy, firms' prices are heterogeneous with respect to the time since their last price adjustment. Table 1 summarizes key notations concerning the dynamics of the price-duration distribution.

Duration	Hazard Rate	Non-adj. Rate	Survival Rate	Distribution
j	h_j	α_j	S_j	$\theta(j)$
0	0	1	1	$\theta(0)$
1	h_1	$\alpha_1 = 1 - h_1$	$S_1 = \alpha_1$	$\theta(1)$
\vdots	\vdots	\vdots	\vdots	\vdots
j	h_j	$\alpha_j = 1 - h_j$	$S_j = \prod_{i=0}^j \alpha_i$	$\theta(j)$
\vdots	\vdots	\vdots	\vdots	\vdots
J	$h_J = 1$	$\alpha_J = 0$	$S_J = 0$	$\theta(J)$

Table 1: Notations of the Dynamics of Price-vintage-distribution.

Using the notation defined in table 1, and also denoting the distribution of price durations at the beginning of each period by $\Theta_t = \{\theta_t(0), \theta_t(1) \dots \theta_t(J)\}$, we can derive the ex-post distribution of firms after price adjustments ($\tilde{\Theta}_t$) as

$$\tilde{\theta}_t(j) = \begin{cases} \sum_{i=1}^J h_i \theta_t(i) , & \text{when } j = 0 \\ \alpha_j \theta_t(j) , & \text{when } j = 1 \dots J. \end{cases} \quad (15)$$

Intuitively, those firms reoptimizing their prices in period t are labeled with 'Duration 0', and the proportion of those firms is given by hazard rates from all duration groups multiplied by their corresponding densities. The firms left in each duration group are the firms that do not adjust their prices. When period t is over, this ex-post distribution, $\tilde{\Theta}_t$, becomes the ex-ante distribution for the new period, Θ_{t+1} . All price duration groups move to the next one, because all prices age by one period.

As long as the hazard rates lie between zero and one, dynamics of the price-duration distribution can be viewed as a Markov process with an invariant distribution, Θ , and is obtained by solving $\theta_t(j) = \theta_{t+1}(j)$. It yields the stationary price-duration distribution $\theta(j)$ as follows:

$$\theta(j) = \frac{S_j}{\sum_{j=0}^{J-1} S_j}, \text{ for } j = 0, 1 \dots J-1. \quad (16)$$

Here, I give a simple example. When $J = 3$, then we have the stationary price-duration distribution $\Theta = \left\{ \frac{1}{1+\alpha_1+\alpha_1\alpha_2}, \frac{\alpha_1}{1+\alpha_1+\alpha_1\alpha_2}, \frac{\alpha_1\alpha_2}{1+\alpha_1+\alpha_1\alpha_2} \right\}$.

Let's assume the economy converges to this invariant distribution fairly quickly, so that regardless of the initial price-duration distribution, I only consider the economy with the invariant distribution of price durations.

2.3.2 The Optimal Pricing under the General Form of Nominal Rigidity

Given the general form of nominal rigidity introduced above, the only heterogeneity among firms is the time when they last reset their prices, j . Firms in price duration group j share the same probability of adjusting their prices, h_j , and the distribution of firms across durations is given by $\theta(j)$.

In a given period when a firm is allowed to reoptimize its price, the optimal price chosen should reflect the possibility that it will not be re-adjusted in the near future. Consequently, adjusting firms choose optimal prices that maximize the discounted sum of real profits over the time horizon in which the new price is expected to be fixed. The probability that the new price will be fixed at least for j periods is given by the survival function, S_j , defined in table 1.

Here, I setup the maximization problem of an adjuster as follows:

$$\max_{P_t^*} E_t \sum_{j=0}^{J-1} S_j Q_{t,t+j} \left[Y_{t+j|t}^d \frac{P_t^*}{P_{t+j}} - \frac{TC_{t+j}}{P_{t+j}} \right].$$

Where E_t denotes the conditional expectation based on the information set in period t , and $Q_{t,t+j}$ is the stochastic discount factor appropriate for discounting real profits from t to $t+j$. An adjusting firm maximizes the profits subject to the demand for its intermediate good in period $t+j$ given that the firm resets the price in period t and can be expressed as.

$$Y_{t+j|t}^d = \left(\frac{P_t^*}{P_{t+j}} \right)^{-\eta} Y_{t+j}.$$

This yields the following first order necessary condition for the optimal price:

$$P_t^* = \frac{\eta}{\eta-1} \frac{\sum_{j=0}^{J-1} S_j E_t [Q_{t,t+j} Y_{t+j} P_{t+j}^{\eta-1} MC_{t+j}]}{\sum_{j=0}^{J-1} S_j E_t [Q_{t,t+j} Y_{t+j} P_{t+j}^{\eta-1}]}, \quad (17)$$

where MC_t denotes the nominal marginal cost. The optimal price is equal to the markup multiplied by a weighted sum of future marginal costs, whose weights depend on the survival rates. In the Calvo case, where $S_j = \alpha^j$, this equation reduces to the Calvo optimal pricing condition.

Finally, given the stationary distribution, $\theta(j)$, aggregate price can be written as a distributed sum of all optimal prices. I define the optimal price which was set j periods ago as P_{t-j}^* . Following the aggregate price index from equation (3), the aggregate price is then obtained by:

$$P_t = \left(\sum_{j=0}^{J-1} \theta(j) P_{t-j}^{*1-\eta} \right)^{\frac{1}{1-\eta}}. \quad (18)$$

2.4 New Keynesian Phillips Curve

To analyze the effects of the general form of nominal and real rigidities on the inflation dynamics, I derive the New Keynesian Phillips curve from log-linearized equations (17) and (18) around the zero-inflation steady state⁸. Defining $\hat{x}_t \equiv \log X_t - \log \bar{X}$, I obtain the generalized NKPC, reflecting the general form of nominal rigidity and real rigidity introduced in the model.

$$\begin{aligned} \hat{\pi}_t = & \sum_{k=0}^{J-1} \frac{\theta(k)}{1-\theta(0)} E_{t-k} \left[\sum_{j=0}^{J-1} \frac{\beta^j S_j}{\Psi} \widehat{mc}_{t+j-k} + \sum_{i=1}^{J-1} \sum_{j=i}^{J-1} \frac{\beta^j S_j}{\Psi} \hat{\pi}_{t+i-k} \right] \\ & - \sum_{k=2}^{J-1} \Phi(k) \hat{\pi}_{t-k+1}, \end{aligned} \quad (19)$$

$$\text{where} \quad : \quad \Phi(k) = \frac{\sum_{j=k}^{J-1} S_j}{\sum_{j=1}^{J-1} S_j} \quad \text{and} \quad \Psi = \sum_{j=0}^J \beta^j S(j).$$

The generalized New Keynesian Phillips curve, equation (19), involves a much more complex structure than the NKPC in the Calvo model⁹. Current inflation depends not only on current marginal cost and inflation, but also on lagged inflation and a complex weighted sum of expectations on inflation and marginal costs. To see the dynamic structure more clearly, I give an example where $J = 3$:

$$\begin{aligned} \hat{\pi}_t = & \frac{1}{(\alpha_1 + \alpha_1 \alpha_2) \Psi} \widehat{mc}_t + \frac{\alpha_1}{(\alpha_1 + \alpha_1 \alpha_2) \Psi} \widehat{mc}_{t-1} + \frac{\alpha_1 \alpha_2}{(\alpha_1 + \alpha_1 \alpha_2) \Psi} \widehat{mc}_{t-2} \\ & + \frac{1}{\alpha_1 + \alpha_1 \alpha_2} E_t \left(\frac{\beta \alpha_1}{\Psi} \widehat{mc}_{t+1} + \frac{\beta^2 \alpha_1 \alpha_2}{\Psi} \widehat{mc}_{t+2} + \frac{\beta \alpha_1 + \beta^2 \alpha_1 \alpha_2}{\Psi} \hat{\pi}_{t+1} + \frac{\beta^2 \alpha_1 \alpha_2}{\Psi} \hat{\pi}_{t+2} \right) \\ & + \frac{\alpha_1}{\alpha_1 + \alpha_1 \alpha_2} E_{t-1} \left(\frac{\beta \alpha_1}{\Psi} \widehat{mc}_t + \frac{\beta^2 \alpha_1 \alpha_2}{\Psi} \widehat{mc}_{t+1} + \frac{\beta \alpha_1 + \beta^2 \alpha_1 \alpha_2}{\Psi} \hat{\pi}_t + \frac{\beta^2 \alpha_1 \alpha_2}{\Psi} \hat{\pi}_{t+1} \right) \\ & + \frac{\alpha_1 \alpha_2}{\alpha_1 + \alpha_1 \alpha_2} E_{t-2} \left(\frac{\beta \alpha_1}{\Psi} \widehat{mc}_{t-1} + \frac{\beta^2 \alpha_1 \alpha_2}{\Psi} \widehat{mc}_t + \frac{\beta \alpha_1 + \beta^2 \alpha_1 \alpha_2}{\Psi} \hat{\pi}_{t-1} + \frac{\beta^2 \alpha_1 \alpha_2}{\Psi} \hat{\pi}_t \right) \\ & - \frac{\alpha_1 \alpha_2}{\alpha_1 + \alpha_1 \alpha_2} \hat{\pi}_{t-1}, \end{aligned}$$

$$\text{where} \quad : \quad \Psi = 1 + \beta \alpha_1 + \beta^2 \alpha_1 \alpha_2.$$

All coefficients are expressed in terms of non-adjustment rates ($\alpha_j = 1 - h_j$) and the subjective discount factor, β . In the empirical analysis, α_j 's are identifiable through estimating the

⁸Detailed derivation is shown in Yao (2009).

⁹Yao (2009) shows that, under the assumption of a constant hazard function, this version of the NKPC can be reduced to the Calvo NKPC, because lagged inflation terms exactly cancel the terms of lagged expectations out.

distributional weights of aggregate variables and expectations at different lags. After I obtain the estimates for the hazard rates, h_j , I can calculate the implied distribution of price durations, $\theta(j)$, by using equation (16).

2.5 Equilibrium and Log-linearized Equations

The general equilibrium system consists of equilibrium conditions derived from the optimization problems of economic agents, market clearing conditions and a monetary policy equation. Market clearing conditions require real prices clear the factor and good markets, while monetary policy determines nominal value of the real economy. I choose a Taylor rule to close the model. Equation (20) is motivated by the interest rate smoothing specification for the Taylor rule¹⁰, which specifies a policy rule that the central bank uses to determine the nominal interest rate in the economy, where ϕ_π and ϕ_y denote short-run responses of the monetary authority to log deviations of inflation and the output gap, and q_t is a sequence of *i.i.d.* white noise with zero mean and a finite variance $(0, \sigma_q^2)$.

$$I_t = I_{t-1}^{\rho_i} \left[\left(\frac{P_t}{P_{t-1}} \right)^{\phi_\pi} \left(\frac{Y_t}{\bar{Y}} \right)^{\phi_y} \right]^{1-\rho_i} e^{q_t} \quad (20)$$

After log-linearizing those equilibrium equations around the flexible-price steady state, log-linearized general equilibrium system consists of the NKPC, equation (21), real marginal cost, equation (22), the household's intertemporal optimization condition, equation (23), the Taylor rule, equation (20), and exogenous stochastic processes. In the IS curve, I add an exogenous shock, d_t , to represent real aggregate demand disturbances¹¹.

$$\hat{\pi}_t = \sum_{k=0}^{J-1} \frac{\theta(k)}{1-\theta(0)} E_{t-k} \left[\sum_{j=0}^{J-1} \frac{\beta^j S_j}{\Psi} \widehat{mc}_{t+j-k} + \sum_{i=1}^{J-1} \sum_{j=i}^{J-1} \frac{\beta^j S_j}{\Psi} \hat{\pi}_{t+i-k} \right] - \sum_{k=2}^{J-1} \Phi(k) \hat{\pi}_{t-k+1} \quad (21)$$

$$\widehat{mc}_t = \frac{\eta(1-a) + a}{\eta(1-a) + a(1+\phi)} [(\delta + \phi)(1-a)\hat{c}_t - (1+\phi)\hat{z}_t] \quad (22)$$

$$\delta E_t [\hat{y}_{t+1}] = \delta \hat{y}_t + (\hat{i}_t - E_t [\hat{\pi}_{t+1}]) + d_t \quad (23)$$

$$\hat{i}_t = (1 - \rho_i) (\phi_\pi \hat{\pi}_t + \phi_y \hat{y}_t) + \rho_i \hat{i}_{t-1} + q_t \quad (24)$$

$$\hat{z}_t = \rho_z * \hat{z}_{t-1} + \epsilon_t \quad \text{where } \epsilon_t \sim N(0, \sigma_z^2) \quad (25)$$

$$d_t = \rho_d * d_{t-1} + \varepsilon_t \quad \text{where } \varepsilon_t \sim N(0, \sigma_d^2) \quad (26)$$

$$q_t \sim N(0, \sigma_q^2) \quad (27)$$

All parameters in the model have a structural interpretation. I collect the structure parameters into a vector $\mu = (a, \beta, \delta, \phi, \eta, \phi_\pi, \phi_y, \rho_i, \alpha_{js})$. In the empirical study, I am interested in estimating values for those structural parameters by using the Bayesian approach.

¹⁰See: the empirical work by Clarida et al. (2000)

¹¹Introducing this shock is not necessary for the theoretical model, but, in the Bayesian estimation, due to the singularity problem I need three shocks for three observables.

3 Estimation

In this section, I first describe the data and econometric procedure used to estimate the model, and then present and analyze the results.

3.1 Bayesian Inference

I apply the Bayesian approach, set forth by DeJong et al. (2000), Schorfheide (2000) and Fernandez-Villaverde and Rubio-Ramirez (2004) among others, to estimate the structural parameters of the DSGE model. The Bayesian estimation is based on combining information gained from maximizing likelihood of the data and additional information about the parameters (the prior distribution). The main steps of this approach are as follows:

First, the linear rational expectation model is solved by using standard numerical methods (See: e.g. Uhlig, 1998 and Sims, 2002) to obtain the reduced form equations in its predetermined and exogenous variables.

For example, the linearized DSGE model can be written as a rational expectations system in the form

$$\Upsilon_0(\mu)S_t = \Upsilon_1(\mu)S_{t-1} + \Upsilon_\epsilon(\mu)\epsilon_t + \Upsilon_\omega(\mu)\omega_t. \quad (28)$$

Here, S_t is a vector of all endogenous variables in the model, such as \hat{y}_t , $\hat{\pi}_t$, \hat{i}_t , etc. The vector ϵ_t stacks the innovations of the exogenous processes and ω_t is composed of one-period-ahead rational expectations forecast errors. Entries of $\Upsilon(\mu)$ matrices are functions of structural parameters in the model. The solution to (28) can be expressed as

$$S_t = \Psi_1(\mu)S_{t-1} + \Psi_\epsilon(\mu)\epsilon_t. \quad (29)$$

The second step involves writing the model in state space form. This is to augment the solution equation (29) with a measurement equation, which relates the theoretical variables to a vector of observables Y_obs_t .

$$Y_obs_t = A(\mu) + BS_t + CV_t. \quad (30)$$

Where $A(\mu)$ is a vector of constants, capturing the mean of S_t , and V_t is a set of shocks to the observables, including measurement errors.

Third, when we assume that all shocks in the state space form are normally distributed, we can use the Kalman filter (Sargent, 1989) to evaluate the likelihood function of the observables $\mathcal{L}(\mu|Y_obs^T)$. In contrast to other maximum likelihood methods, the Bayesian approach combines the likelihood function with prior densities $p(\mu)$, which includes all extra information about the parameters of interest. The posterior density $p(\mu|Y_obs^T)$ can be obtained by applying Bayes' theorem

$$p(\mu|Y_obs^T) \propto \mathcal{L}(\mu|Y_obs^T) p(\mu). \quad (31)$$

In the last step, μ is estimated by maximizing the likelihood function given data $\mathcal{L}(\mu|Y_obs^T)$ reweighted by the prior density $p(\mu)$, in that numerical optimization methods are used to find

the posterior mode for μ and the inverse Hessian matrix. Finally, the posterior distribution is generated by using a random-walk Metropolis sampling algorithm¹².

3.2 Data

According to my empirical model and research questions to be addressed in this paper, I choose following three observables: the growth rate of real GDP per capita, the inflation rate and nominal interest rate series for the U.S. over the period 1955.Q1 - 2008.Q4¹³. In estimating a structural price setting model, it is essential to avoid spurious influences due to shifts in the monetary policy regime especially when estimating backward-looking pricing (See: Erceg and Levin, 2003). To avoid this problem, I follow Lubik and Schorfheide (2005) to split the sample into two sub-samples. The first sub-sample (DS1) ranges from 1955.Q1 to 1982.Q4, while the second (DS2) is based on the periods from 1983.Q1 to 2008.Q4. I plot all data series in figure 2¹⁴.

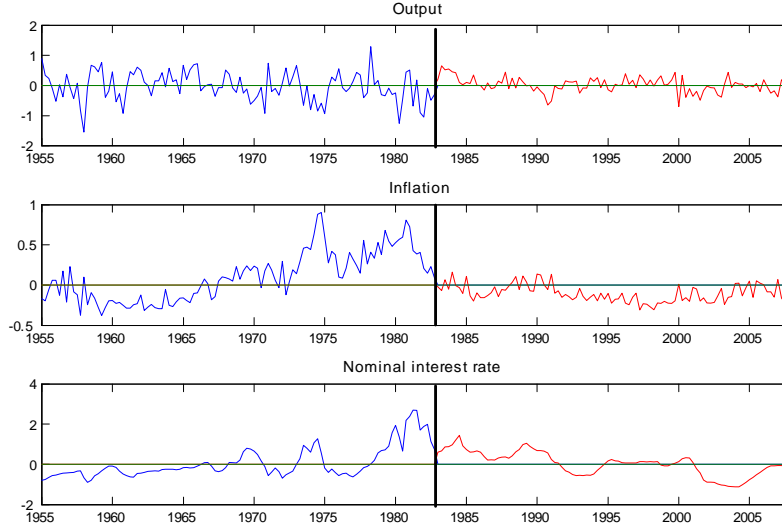


Figure 2: Data Plot

Based on the way I construct the empirical model and the definition of variables, the measurement equations are defined as follows:

$$y_obs = \hat{y}_t - \hat{y}_{t-1}$$

$$\pi_obs = \hat{\pi}_t$$

$$i_obs = \hat{i}_t.$$

¹²I implement the Bayesian estimation procedure discussed above by using the MATLAB based package DYNARE, which is available at: <http://www.cepremap.cnrs.fr/dynare/>

¹³Details on the construction of the data set are provided in Appendix (B).

¹⁴In this figure, data series are detrended by a common linear trend, but in the empirical analysis I detrend each sub-sample by a separate linear trend.

3.3 Priors

The priors I choose are in line with the mainstream values used in the Bayesian literature (e.g. Smets and Wouters, 2007 and Lubik and Schorfheide, 2005). They are centered around the average value of estimates of micro and macro data with fairly loose standard deviations. The marginal prior densities for the structural parameters are listed in table 2.

parameters	prior_dist.	mean	st.dev	parameters	prior_dist.	mean	st.dev
δ	gamma	1.5	0.375	ρ_i	beta	0.5	0.1
ϕ	normal	0.5,1.5	1.0	ρ_z	beta	0.8	0.1
a	beta	0.56	0.20	ρ_d	beta	0.5	0.1
α_j	beta	0.5	0.26	σ_z	invgam	0.1	2.0
ϕ_π	Gamma	1.5	0.1	σ_m	invgam	0.1	2.0
ϕ_y	Gamma	0.125	0.1	σ_d	invgam	0.1	2.0

Table 2: Priors of Parameters.

I fix two parameters in advance. The discount factor β is equal to 0.99, implying an annual steady state real interest rate of 4%. The elasticity of substitution between intermediate goods is set to be 10, implying an average mark-up of around 11%. Both are common values used in the literature.

The prior distributions of the preference parameters are largely in line with Smets and Wouters (2007). The intertemporal elasticity of substitution, δ , is set to follow a gamma distribution with mean 1.5 and a standard error of 0.375; The inverse elasticity of labour supply, ϕ , is assumed to be normally distributed around the mean of 0.5 and 1.5. A mean of 0.5 reflects high elasticities of labor supply ($\frac{1}{\phi} = 2$) that is motivated by using balanced growth path considerations in the macro literature, while $\frac{1}{\phi} = \frac{1}{1.5}$ is typically estimated in the micro-labor studies (See: e.g. Blundell and Macurdy, 1999). For both cases I set a large standard error of 1.0.¹⁵

I choose a beta distribution with the support between zero and one as the prior for the share of intermediate inputs, a . I set the mean to 0.56, reflecting the weighted average revenue share of intermediate inputs in the U.S. input-output table (Nakamura and Steinsson, 2008b). The standard deviation is equal to 0.20. The priors for the non-adjustment ratios, α_j , are chosen based on micro evidence on the mean frequency of price adjustments, reported by Bils and Klenow (2004). They find that the U.S. sectoral prices on average last only 2 quarters, which implies the hazard rate is equal to 0.5. I set the loose prior to all α_j 's with the same mean, so that these priors reflect the view of a constant-hazard pricing model, such as in the Calvo model. By choosing a fairly large standard deviation (0.26) for hazard rates, I allow the data to speak out quite freely about the magnitudes of hazard rates over the time horizon specified in the model. The prior on the coefficients in the monetary policy reaction function are standard. The priors for ϕ_π and ϕ_y are centered at the values commonly associated with the Taylor-rule. This rule also allows for interest rate smoothing with a prior mean of 0.5 and a standard deviation of 0.1.

¹⁵The reason I use two priors for ϕ is that, as shown in the estimation results, the data does not provide accurate information on this parameter, so that the prior mean largely predominates the posterior mode of ϕ . Therefore, I set two different priors to check the robustness of my other results to the value of ϕ .

Finally, I assume that the standard errors of the innovations follow an inverse-gamma distribution with a mean of 0.1 and two degrees of freedom. The persistence of the AR(1) process of the productivity shock is beta-distributed with a mean of 0.8 and the standard deviation of 0.1, and the persistence of the AR(1) process of the aggregate demand shock is beta-distributed with a mean of 0.5 and the standard deviation of 0.1.

3.4 Estimation Results

By applying the methodology described above, I proceed to gauge the degree of real and nominal rigidity in terms of the estimated structural parameters. The posterior modes of parameters are calculated by maximizing the log likelihood function of the data, and then the posterior distributions are simulated using the “Metropolis-Hastings” algorithm. The results presented here are based on 200,000 draws and the average acceptance rate is around 0.4.

The posterior mode, mean and 5%, 95% quantiles of the 18 estimated parameters are reported in tables 6 and 7 for both subsamples (DS1, DS2). In figures 4 and 5, I plot the histograms of all parameters obtained by the Metropolis-Hastings simulations. In figures 6 and 7, I present results of the “multivariate diagnostic plot” that reports an aggregate measure of convergence based on the eigenvalues of the variance-covariance matrix of each parameter. The horizontal axis represents the number of Metropolis-Hastings iterations, and the vertical axis gives the measure of the parameter moments, starting from the initial value of the Metropolis-Hastings iterations. In this case, we obtain convergence and relative stability in all measures of the parameter moments.

A visual comparison of prior and posterior distributions suggests that the time series data provides weak information on the inverse elasticity of labor supply, ϕ , and the monetary policy parameter, ϕ_π , but they are very informative about the real and nominal rigidities in terms of the estimated parameters. Focusing on the results from the period after 1983, the estimated share of intermediate inputs is around 0.91, and is largely consistent with the value argued for by Basu (1995). The elasticity of intertemporal substitution is quite high (3.36) and the inverse elasticity of labor supply is 0.83 for the posterior mode. Together with the fixed value $\eta = 10$, they imply the real rigidity parameter, $\gamma\kappa_1$, is equal to 0.254, and translates to a modest level of strategic complementarity. I turn now to the nominal rigidity that is represented by the estimates of non-adjustment rates, α_j . Contrary to the prior distributions, which are motivated by the Calvo model where all hazard rates are constant over time, the estimates reveal that the hazard function changes shape over time and the data strongly advocates a non-constant hazard function. The estimated hazard function has a mean of roughly 15% per quarter which is broadly consistent with the estimates of the standard NK models. More importantly, price reset hazards vary substantially around this mean, depending on how long the non-adjustment spell is. The hazard rate is high one quarter after the price adjustment (about 80%), suggesting that there is a large portion of firms revising their prices frequently (quarter-by-quarter). Afterwards, the hazard rates stay low for the next three consecutive quarters (around 10%) and rise at the 4th and 6th quarters after the price adjustment. This is evidence that a considerable number of firms adjust prices on a periodical basis and that both implicit and/or explicit price contracts exist within the economy. As to the shape of the hazard function, with the exception of periodical spikes, hazard rates are largely constant but slightly increasing towards the end of the time

horizon. The estimated shape of the hazard function for sub-sample DS1 exhibits a somewhat different pattern. I discuss this aspect of estimates in detail in a later section.

Finally, the estimated monetary policy reaction function is consistent with the common view of the Taylor rule. Monetary policy after 1983 responds strongly to the deviation of inflation (1.647), but not much to the output gap (0.03). There is a considerable degree of interest rate smoothing, as the posterior mode of ρ_i is around 0.7. It is noteworthy to address that the estimates of the monetary policy function are considerably different when using the ‘DS1’ data set. Monetary policy appears to react more weakly to the inflation gap, but much more strongly to the output gap (0.197). Besides, it has a slightly weaker interest rate smoothing component (0.66) than in the post 1983 periods.

3.5 Robustness Tests

In this section, I first test the robustness of the estimates under alternative setups regarding different priors, and then I check the sensitivity of identified real and nominal rigidities to the different truncation points on the price duration as well as the choice of labor supply elasticity.

3.5.1 Alternative Priors and Model Setups

Parameter	M(1) Benchmark	M(2) $\phi = 1.5$	M(3) $\eta = 10$	M(4) $\eta = 6$	M(5) $\alpha = 0.5$
a	0.9137 (0.0451)	0.8987 (0.0467)	0.9137 (0.0451)	0.9128 (0.0464)	0.8652 (0.0547)
η	10	10	9.9761 (0.4994)	5.9603 (0.4984)	10
δ	3.3694 (0.4729)	3.3750 (0.4744)	3.3694 (0.4728)	3.3721 (0.4726)	3.1049 (0.4605)
ϕ	0.8305 (0.8776)	1.6710 (0.9463)	0.8305 (0.8778)	0.8352 (0.8807)	0.9892 (0.8377)
ϕ_π	1.6470 (0.0974)	1.6479 (0.0976)	1.6470 (0.0974)	1.6464 (0.0974)	1.6982 (0.0933)
ϕ_y	0.0306 (0.0429)	0.0289 (0.0408)	0.0306 (0.0430)	0.0314 (0.0442)	0.059 (0.0414)
α_1	0.1951 (0.0772)	0.2044 (0.0782)	0.1951 (0.0772)	0.1907 (0.0765)	0.5
α_2	0.9087 (0.1384)	0.9114 (0.1345)	0.9087 (0.1384)	0.9074 (0.1402)	0.5
α_3	0.9256 (0.1198)	0.9282 (0.1155)	0.9256 (0.1198)	0.9244 (0.1218)	0.5
α_4	0.9174 (0.1351)	0.9204 (0.1300)	0.9174 (0.1351)	0.9161 (0.1375)	0.5
α_5	0.4302 (0.3891)	0.4449 (0.3719)	0.4302 (0.3891)	0.4232 (0.3977)	0.5
α_6	0.7257 (0.4154)	0.7399 (0.3917)	0.7257 (0.4154)	0.7189 (0.4268)	0.5
α_7	0.2825 (0.4602)	0.2745 (0.4447)	0.2825 (0.4602)	0.2865 (0.4676)	0.5
Log Margin. Likeli.	66.10	66.26	66.10	66.25	59.27

Table 3: Sensitivity Check of the Posterior Modes

Table 3 reports results of the sensitivity analysis in the following steps: first, I check the prior

sensitivity by altering the prior mean, ϕ , to 1.5. I choose to check this parameter because of the conflict between micro and macro calibration values. The first two columns in the table compare the results from the two alternative priors. All estimates remain similar in both cases except for ϕ . When using 0.5 as the prior mean, the posterior mode is equal to 0.8305 with a standard deviation of 0.8776. When setting the prior mean to 1.5, on the other hand, the posterior mode is equal to 1.6710 with a standard deviation of 0.9463. Next, I check whether fixing η affects the estimation results. To do that, instead of setting η to 10, I now allow for estimating the value of η with the prior mean of 6 and 10 - two common values used in NK models. The third and fourth columns report almost identical results with the exception of η . These results manifest the identification problem of these two parameters in this empirical framework. In the case of ϕ , the choice of the prior only marginally affects the joint data density, while, in the case of η , inclusion of this parameter in the estimation does not matter at all, meaning that the population objective function may be independent of this parameter. From these results, we learn that the identification of the hazard function in this model is robust to the choice of these two structural parameters in the selected range.

Finally, I change the model setup by fixing the hazard rates to the value of 0.5, implying an average duration of 2 quarters¹⁶. As seen in the last column, fixing hazards does not significantly affect the estimates of other structural parameter. But, in terms of log marginal likelihood, this fixed-hazard setup is clearly less favorable by the data. In the last row of the table, I report the log marginal likelihood of the data for each model. It shows that changing priors of η and ϕ only marginally affects the data density, but the data gives strong support of the flexible hazard model M(1) as opposed to the fixed-hazard model M(5). The Bayes factor in favor of the flexible hazard model is approximately by the factor of 10^3 .

3.5.2 Truncation Points and Real/Nominal Rigidity

In this session, I address an issue first raised by Carvalho and Dam (2008), in which they emphasize that allowing for prices to last more than 4 quarters is crucial to avoid estimates implying too little average nominal rigidity and too much real rigidity. In other words, the choice of maximum price duration, J , is not innocuous for the estimates regarding nominal and real rigidities. Coenen et al. (2007), for example, estimate a generalized Calvo model with the maximum price duration of 4 quarters. As a result, their estimates imply an extremely high level of real rigidity (0.004 for the U.S. estimates). Carvalho and Dam (2008) demonstrate, however, that by allowing for a maximum duration of 6 or 8 quarters, the estimates of real rigidity decline significantly. For example, the median level of the real rigidity parameter in the posterior distribution rises in the case of $J = 6$, from 0.006 to 0.021 and when $J = 8$, it increases even further to 0.042. Nevertheless, these results are still quite low regarding the values deemed plausible in the macro literature.

In table 4, I present some new results from the Bayesian estimation. I report the estimation results regarding nominal and real rigidities with respect to models with the maximum price

¹⁶I call it the pseudo-Calvo model because, in this case, I truncate the hazard function at the 6th quarter. As a result, it is not exactly equivalent to the Calvo model, which implies an infinite horizon for the hazard function. This pseudo-Calvo can be view as an approximation of the real Calvo model. I conduct also the pseudo-Calvo model with longer horizons, but it does not change the main conclusion.

duration of 4, 6, and 8 quarters. The first three columns present the results when setting the prior for the inverse elasticity of labor supply to 0.5, and the last three columns report the same results for $\phi = 1.5$ as a sensitivity check. Both result panels confirm the conclusions drawn by Carvalho and Dam (2008) – that an over restrictive truncation of the maximum duration tends to overestimate real rigidity at the expense of nominal rigidity. As seen in the table, even though the shape of the hazard function stays relatively stable in models with a different truncation point, the implied average duration of prices increases significantly with a rising maximum duration. When $\phi = 0.5$, for example, the mean duration of sticky prices is only 4.42 months in the model of $J = 4$, while it increases to 6.88 months in the model with $J = 8$. By contrast, the real rigidity parameter, $\gamma\kappa_1$, increases, which means strategic complementarity weakens with an increase of maximum duration. It is however, worthy of noting, that the real rigidity obtained in this full information estimation is broadly in line with the plausible values in the literature. They range between 0.155 to 0.286 in different setups, but all those values fall within the reasonable range of strategic complementarity in price decisions.

parameter	$\phi = 0.5$			$\phi = 1.5$		
	J=4	J=6	J=8	J=4	J=6	J=8
α_1	0.127	0.182	0.195	0.134	0.210	0.204
α_2	0.882	0.904	0.909	0.885	0.910	0.911
α_3	0.834	0.910	0.926	0.835	0.914	0.928
α_4	1	0.899	0.917	1	0.904	0.920
α_5		0.236	0.430		0.248	0.445
α_6		1	0.726		1	0.740
α_7			0.283			0.275
α_8			1			1
Mean Duration (months)	4.42	5.98	6.88	4.48	6.29	7.03
γ	0.753	0.784	0.701	0.544	0.599	0.560
κ_1	0.206	0.251	0.363	0.313	0.347	0.511
Real Rigidity ($\gamma\kappa_1$)	0.155	0.197	0.254	0.170	0.208	0.286
Bayes' factor	1	30.1	175.9	1	24.5	182.7

Table 4: Effects of Truncation on Nominal and Real Rigidities

In the last row, I report the Bayes' factors based on the model with a maximum duration of 4 quarters as the benchmark case. The Bayes' factors show that the data strongly supports the models with longer maximum durations. The factor is around 25-30 for models with a maximum duration of 6 quarters and 180 for models with a maximum duration of 8 quarters. In light of this result, I choose to estimate the model with an 8-quarter-hazard-function in the next section, implying a maximum price duration of 9 quarters¹⁷.

¹⁷It is worth of noting that it is not true that the longer maximum duration is chosen, better the result will be. This is because the longer maximum-duration has also costs in terms of computational burdens and identification problems.

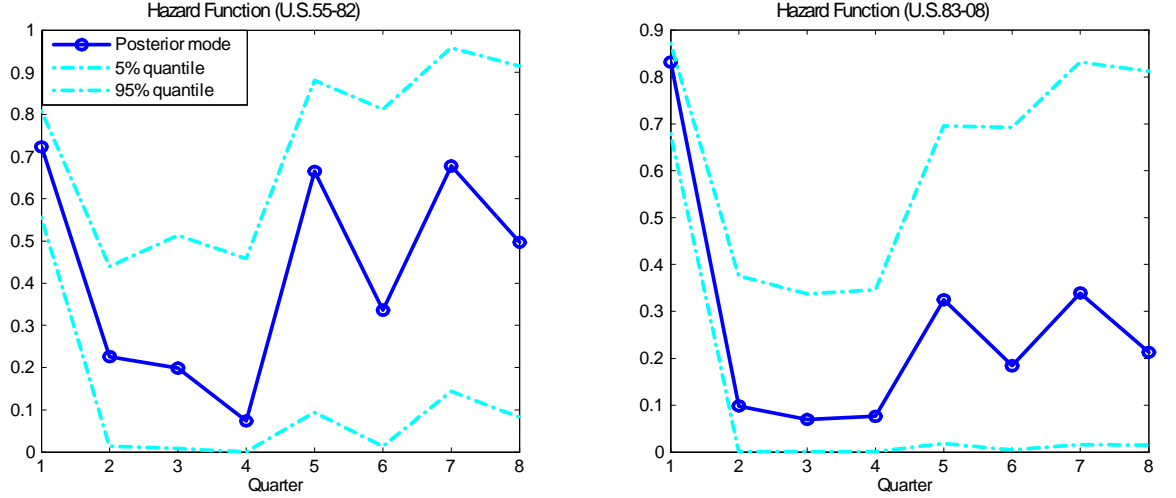


Figure 3: Comparison of Hazard Functions

3.6 Hazard Functions

In this section, I compare the estimates of hazard functions from the two sub-samples. As discussed in the introduction, empirical work using micro data sets gives different evidence on the shape of the empirical hazard function. For example, Cecchetti (1986) used newsstand prices of magazines in the U.S. and Goette et al. (2005) examined Swiss restaurant prices. Both studies find strong support for increasing hazard functions. By contrast, recent studies using more comprehensive micro data find that hazard functions are first downward sloping and then mostly flat, interrupted periodically by spikes (See, e.g.: Campbell and Eden, 2005, Alvarez et al., 2006 and Nakamura and Steinsson, 2008a). Studies using earlier data tend to support a different picture of the hazard function as opposed to those using data sets from more recent periods. This is evidence that the shape of hazard functions depends on the underlying economic conditions, such as inflation rates, and is therefore changing over the time periods of the collected data. Here, I use the longer time series data to estimate the hazard function consistently and compare the results.

The pattern of hazard functions is shown in figure (3). In the right panel, I plot the posterior modes of hazard rates in the post-1983 period, when the inflation rate is modest and stable. It is slopping downwards in the first two quarters and then slightly increasing in time-since-last-adjustment, but with periodical spikes at the 4th and 6th quarters after the first adjustment. This pattern largely resembles the empirical hazard function from recent micro studies. By contrast, in the left panel, the estimated hazard function for the pre-1983 periods shows a similar pattern, but it exhibits a remarkable increasing trend after the 4th quarter. One interpretation of this finding is that price setting is characterized by both time- and state-dependent aspects, but, in a turbulent economic environment, the state-dependent pricing plays a larger role in price decisions of the sticky sectors. In this empirical exercise, I apply the generalized time-dependent model to data sets that are characterized by different macroeconomic conditions. Estimated hazard function changes in its shape in subsamples. Therefore, this framework is

flexible enough to empirically capture the state-dependent feature in the data. Finally, we can also draw conclusion that price stickiness in the economy is substantially variant. Roughly 70% of firms adjust their prices frequently (quarter-by-quarter), while there are also a fair amount of firms adjusting their prices periodically.

3.7 Distribution of Price Durations

Durations	This Model			Carvalho&Dam ¹			Coenen et. al. ²
	J=4	J=6	J=8	J=4	J=6	J=8	J=4 (U.S.)
ω_1	0.750	0.602	0.552	0.583	0.382	0.276	0.98
ω_2	0.095	0.109	0.108	0.156	0.104	0.086	0.00
ω_3	0.085	0.099	0.098	0.036	0.033	0.027	0.01
ω_4	0.070	0.089	0.090	0.225	0.045	0.037	0.01
ω_5		0.081	0.083		0.173	0.156	
ω_6		0.019	0.036		0.264	0.144	
ω_7			0.026			0.143	
ω_8			0.007			0.132	
Mean Duration (months)	4.42	5.98	6.88	5.71	9.95	13.1	4.2

Notes: 1) Results reported here is taken from the Table (4) in the paper.

2) Results reported here is taken from the Table (5) in the paper.

Table 5: Distribution of Price Durations

Finally, I report the distribution of price durations implied by the estimated hazard rates. I calculate them by using formula (16). Table 5 reports the results of the data set DS2 and compares them with results from similar studies in the literature. The first noteworthy fact is that the duration distributions reported in this table do not have the same shape. While distributions in this paper and Coenen et al. (2007) are strictly downward sloping, those in Carvalho and Dam (2008) are U-shaped. When I compare the mean durations implied by these models, my model with 4-quarter-truncation yields a similar result as in Coenen et al. (2007). The average duration is around 4.3 months, close to the evidence reported by Bils and Klenow (2004). However, as I have shown in the previous section, by extending the truncation point, the mean duration implied by the estimates increases. With 8-quarter-truncation, my model produces an average duration of 6.88 months, which is consistent with the evidence presented by Nakamura and Steinsson (2008a), who control the price data for sales and product substitution. Carvalho and Dam (2008)'s distributions, on the other hand, yield much longer mean durations, more than double the size of the mean durations reported from other studies.

Conclusion

In this paper, I study issues related to real and nominal price rigidities by estimating a fully-specified DSGE model with the full information Bayesian approach. I construct a DSGE model featuring nominal rigidity that allows for a flexible hazard function of price setting and real rigidity. The generalized NKPC possesses a rich dynamic structure, with which I can identify the detailed time-profile of hazard rates underlying the aggregate dynamics.

This study reveals some interesting insights, which are absent in the literature. First, by using the aggregate time series data, this empirical model allows for inferring the shape of the hazard function over a long period of time in a consistent way. The estimates for the sub-sample from 1983 to 2008 largely resemble the evidence found in the microeconomic studies using data from similar periods. They reveal that firms adjust their price mainly in a time-dependent manner. By contrast, the results for pre-1983 periods, however, suggest that pricing behavior is very different when the data is characterized by highly volatile inflation. Second, my empirical findings confirm the conclusion drawn by Carvalho and Dam (2008), that an over-restrictive truncation of the maximum duration tends to overestimate real rigidity at the expense of nominal rigidity. The level of real rigidity obtained in my full information estimation is broadly more plausible than those reported by the studies using limited information empirical methods. Therefore, it is useful to use a fully-specified DSGE model to infer real and nominal rigidities underlying the aggregate data.

There are, however, some important caveats. First, in this paper, I show that it is possible to identify the shape of price reset hazard function using only the aggregate data, such as inflation and output gap. This approach works by carefully identifying the effects of lagged inflation and lagged expectations of aggregate variables on inflation through the generalized NKPC. As shown in the empirical results, those effects fade out fairly fast in the data, as a result, hazard rates after the 4th quarter are only weakly identified. Next, identification is a complex issue, because all model's assumptions could affect the validity of the results. In this paper, I use a fairly stylized model with many convenient features. Some of them need to be examined more carefully. For example, if the Taylor rule is suitable for this generalized sticky price model? If not, should a more general formulation of monetary policy be used in the estimation? Moreover, Ascari (2004) shows that trend inflation plays an important role in both the long-run and the short-run inflation dynamics. It might be important to estimate the model taking the trend inflation into account, because it also affects the dynamic structure of the generalized NKPC (See: Yao, 2009). I put these questions in the future research agenda.

A Deviation of Marginal Costs

The labor market is competitive and intermediate input markets are featured by a monopolistic supplier and inter-firm demands, firms are price takers in both factor markets. In each period, firms maximize their real profits in terms of composite consumption goods given factor prices and the production technology (7), solving

$$\max_{N_t(i), M_t(i)} \Pi_t(i) = \frac{P_t(i)}{P_t} Y_t(i) - \frac{W_t}{P_t} L_t(i) - M_t(i).$$

Deriving the F.O.Cs of labor and intermediate inputs yields:

$$\frac{W_t}{P_t} = \frac{1-a}{a} \frac{M_t(i)}{L_t(i)}. \quad (32)$$

Then substituting out $M_t(i)$ by using the production function (7), I obtain the conditional demand function for the labor input

$$L_t(i) = \left(\frac{a}{1-a} \right)^{-a} \frac{Y_t(i)}{Z_t} \left(\frac{W_t}{P_t} \right)^{-a}. \quad (33)$$

Similarly, I can derive the conditional demand function for the intermediate input

$$M_t(i) = \left(\frac{a}{1-a} \right)^{1-a} \frac{Y_t(i)}{Z_t} \left(\frac{W_t}{P_t} \right)^{1-a}. \quad (34)$$

Given these conditional demands for inputs, the production costs can be obtained as follows:

$$TC(W_t, P_t, Y_t(i)) = (1-a)^{a-1} a^{-a} \left(\frac{W_t}{P_t} \right)^{1-a} \frac{P_t Y_t(i)}{Z_t}. \quad (35)$$

It follows that real marginal cost is obtained by taking derivative w.r.t. $Y_t(i)$,

$$mc_t = (1-a)^{a-1} a^{-a} \left(\frac{W_t}{P_t} \right)^{1-a} \frac{1}{Z_t}. \quad (36)$$

Finally, we can substitute real wage out of this expression by using equilibrium labor supply condition (5)

$$mc_t = (1-a)^{a-1} a^{-a} \left(\chi_H L_t^\phi C_t^\delta \right)^{1-a} \frac{1}{Z_t} \quad (37)$$

B Data

The data used in this paper is taken from the FRED (Federal Reserve Economic Data) maintained by the Federal Reserve Bank of St. Louis.

- Growth rate of real GDP per capita: is based on the Real Gross Domestic Product (Series: GDPC1). They are in the unit of billions of chained 2005 dollars, quarterly frequency and seasonally adjusted. To construct per capita GDP, I use the Civilian Noninstitutional Population (Series: CNP16OV) from the Bureau of Labor Statistics, U.S. Department of Labor. The monthly data is converted into quarterly frequency by arithmetic averaging. Per capita real output growth is defined as: $100 \times [\ln(GDP_t/POP_t) - \ln(GDP_{t-1}/POP_{t-1})]$. Finally the series in subsamples are mean-adjusted by a linear trend separately.
- Inflation rate: is calculated by using either the implicit price deflator (Series: GDPDEF) or Consumer Price Index for all urban consumers: all items (Series: CPIAUCSL). The monthly data is converted into quarterly frequency by arithmetic averaging. Inflation rate is defined as $100 \times \ln(P_t/P_{t-1})$. Finally the series in subsamples are mean-adjusted by a linear trend separately.
- Nominal interest rate: is the Effective Federal Funds Rate (Series: FEDFUNDS). The monthly data is converted into quarterly frequency by arithmetic averaging. The data is divided by 4 and then is detrended with the trend inflation calculated by using the Hodrick-Prescott-Filter.

C Tables

Parameters	Prior			Posterior (M-H 200,000)			
	Dist.	Mean	S.D.	Mode	Mean	5%	95%
a	beta	0.56	0.20	0.9137	0.8781	0.7808	0.9805
δ	gamma	1.5	0.375	3.3694	3.2449	2.4431	3.9824
ϕ	normal	0.5	1.0	0.8305	1.0628	-0.2269	2.2943
ϕ_π	normal	1.5	0.1	1.6470	1.6802	1.5303	1.8386
ϕ_y	normal	0.125	0.1	0.0306	0.0398	-0.0310	0.1148
ρ_i	beta	0.5	0.1	0.6987	0.6831	0.6161	0.7497
α_1	beta	0.5	0.26	0.1951	0.2778	0.1420	0.4113
α_2	beta	0.5	0.26	0.9087	0.8204	0.6512	0.9976
α_3	beta	0.5	0.26	0.9256	0.8201	0.6334	0.9993
α_4	beta	0.5	0.26	0.9174	0.7822	0.5463	0.9994
α_5	beta	0.5	0.26	0.4302	0.4732	0.0658	0.8730
α_6	beta	0.5	0.26	0.7257	0.5661	0.1888	0.9878
α_7	beta	0.5	0.26	0.2825	0.4592	0.0286	0.8448
ρ_z	beta	0.8	0.1	0.9922	0.9858	0.9736	0.9988
ρ_d	beta	0.5	0.1	0.8768	0.8635	0.8157	0.9123
σ_z	invgam	0.1	2.0	0.0573	0.0779	0.0253	0.1322
σ_m	invgam	0.1	2.0	0.1590	0.1666	0.1382	0.1937
σ_d	invgam	0.1	2.0	0.1059	0.1191	0.0764	0.1617

Table 6: Posterior Distributions of Parameters (U.S.83-08)

Parameters		Prior		Posterior (M-H200,000)			
	Dist.	Mean	S.D.	Mode	Mean	5%	95%
a	beta	0.56	0.20	0.9914	0.9889	0.9790	0.9985
δ	gamma	1.5	0.375	3.0111	3.0441	2.2801	3.7508
ϕ	normal	0.5	1.0	0.8583	1.0947	-0.2431	2.2961
ϕ_π	normal	1.5	0.1	1.4923	1.5009	1.3380	1.6581
ϕ_y	normal	0.125	0.1	0.1973	0.2079	0.1193	0.2922
ρ_i	beta	0.5	0.1	0.6599	0.6628	0.5999	0.7251
α_1	beta	0.5	0.26	0.2734	0.3297	0.1941	0.4632
α_2	beta	0.5	0.26	0.7729	0.7639	0.5785	0.9843
α_3	beta	0.5	0.26	0.7988	0.7274	0.4910	0.9884
α_4	beta	0.5	0.26	0.9262	0.8088	0.6077	0.9997
α_5	beta	0.5	0.26	0.3298	0.4865	0.1023	0.8890
α_6	beta	0.5	0.26	0.6626	0.5700	0.1975	0.9816
α_7	beta	0.5	0.26	0.3298	0.4615	0.0431	0.8581
ρ_z	beta	0.8	0.1	0.8133	0.7753	0.6781	0.8815
ρ_d	beta	0.5	0.1	0.8723	0.8597	0.8152	0.9063
σ_z	invgam	0.1	2.0	0.0648	0.0884	0.0319	0.1482
σ_m	invgam	0.1	2.0	0.2888	0.2948	0.2584	0.3303
σ_d	invgam	0.1	2.0	0.3351	0.3718	0.2527	0.4804

Table 7: Posterior Distributions of Parameters (U.S.55-82)

D Figures

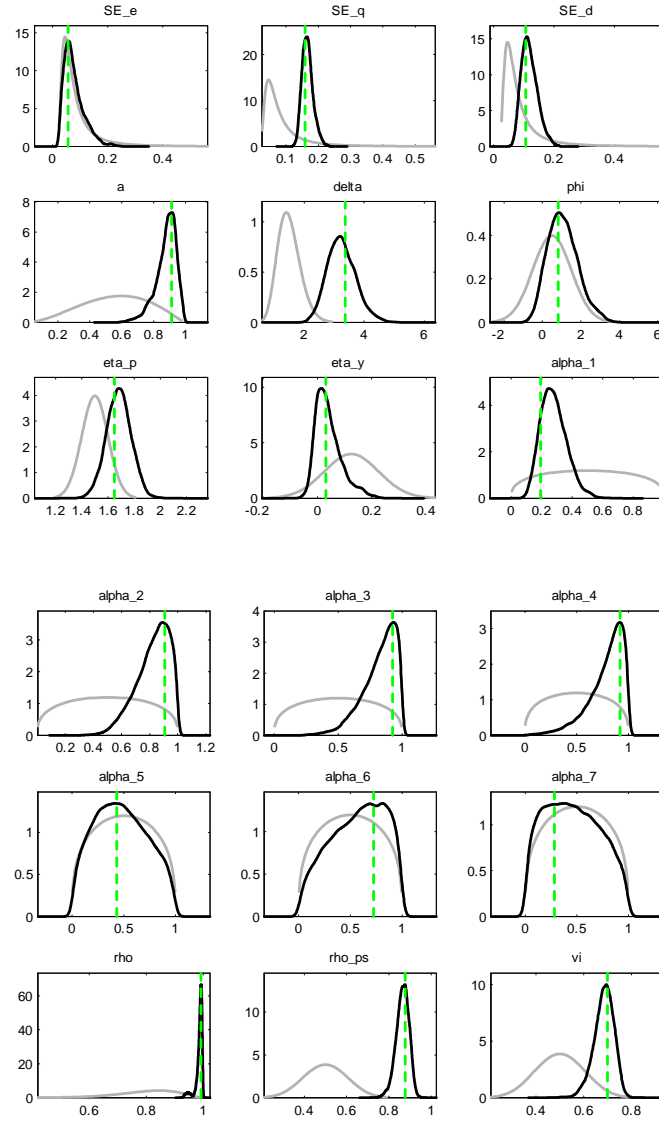


Figure 4: Prior and Posterior Distributions (U.S.83-08)

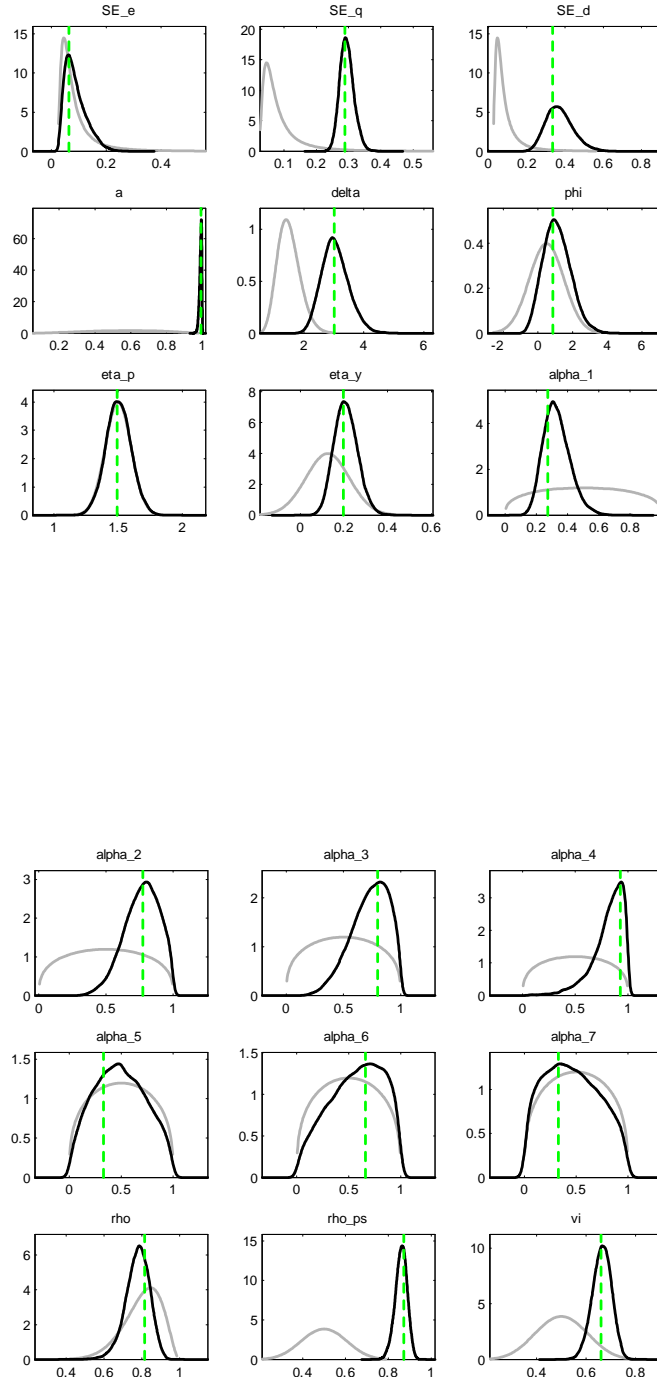


Figure 5: Prior and Posterior Distributions (U.S.55-82)

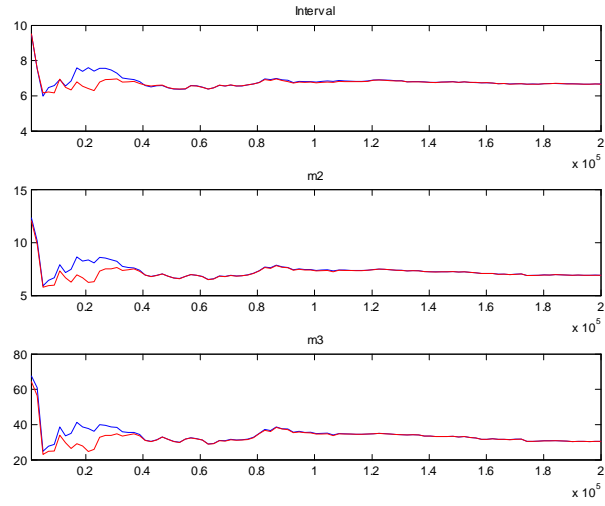


Figure 6: Multivariate Diagnostic Plots (55-82)

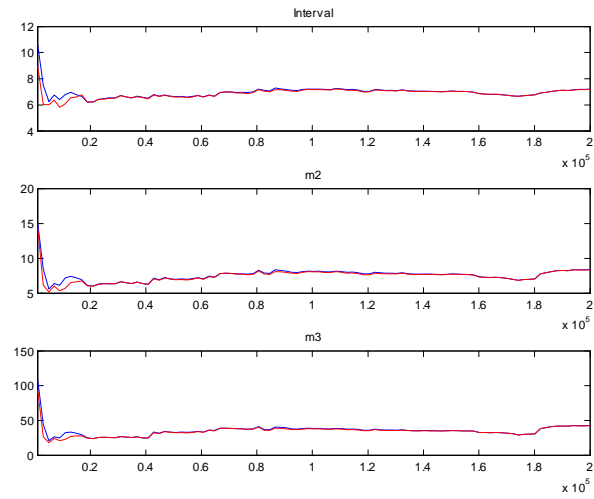


Figure 7: Multivariate Diagnostic Plots (83-08)

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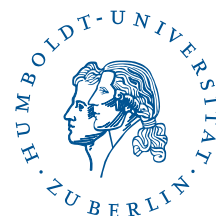
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