ESSAYS ON MONETARY POLICY AND ASSET PRICES

A Dissertation

by

JONG CHIL SON

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

December 2008

Major Subject: Economics

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ABSTRACT

Essays on Monetary Policy and Asset Prices. (December 2008)

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The recent financial and economic turmoil driven by the housing market has led economists to refocus on monetary policy and asset price, including housing prices. The various relationships between monetary policy and asset prices in the U.S. economy are investigated through steady state Bayesian VAR (SS BVAR) and revised Taylor-rule (Forward-looking rule) based on the Generalized Method of Moments (GMM).

The multi-step ahead forecasts using steady state Bayesian VAR (SS BVAR), standard BVAR, and conventional VAR are executed. Equal predictive ability tests following Giacomini and White (2006) verify that the SS BVAR is superior in forecasting performance especially in the long-horizons when compared to the cases of standard BVAR and conventional VAR.

Alternative identifications involving the housing sector are explored in two different ways: an economic theory-based approach and algorithms of inductive causations. The impulse response of housing price and investment to Federal Funds Rates (FFRs) in all alternative identifications illustrate that the magnitudes are relatively smaller, less significant, and shorter when compared to the Choleski case. Also, this finding can be fortified by historical decomposition and conditional forecast analyses

which confirm that the recent high peak in housing prices cannot be well accounted for except by the housing price shock itself. With all these estimation results, it is hard to agree with the argument that the considerable responsibility of the current housing boom and fallout is due to monetary policy shocks. Rather, it can be said that there is still enormous uncertainty between monetary policy and housing prices. Institutional shocks such as fundamental change of mortgage markets including the mobilizing the mortgage debts could probably compose the “uncertainty”.

How does the Fed respond to stock price and inflation movements differently across high and low inflation sub-periods? The replicated linear estimation results of Dupor and Conley (2004)’s indicate that the Fed raises its target interest rate responding to stock price gap with statistical significance. The linear estimation results, however, are not statistically robust to small changes in the breakpoint especially in the inflation coefficient. Thus, a nonlinear model is constructed as an alternative way to relax this problem. Upon the nonlinear framework, the identification of the dominant cause of apparent change in the Fed behavior, between structural change and nonlinearity, is explored. Consequently, both nonlinearity and structural changes matter in an explanation of the Fed’s behavior. Given a structural change, the inflation coefficients’ movements show that the Fed has responded nonlinearly to the expected inflation pressure across the high and low inflation sub-periods, while the stock price gap coefficients’ show an explicit break around the early 1990s in line with Dupor and Conley (2004)’s finding.

DEDICATION

This dissertation is gratefully dedicated to:

my wife, Seung Hee;

and my parents, Jung Mok Son and Soon Ja Woo.

I could not have completed my study without their love, encouragement, and support.

ACKNOWLEDGEMENTS

I would like to acknowledge all those who have helped me in my dissertation. Especially I would like to thank Dr. Dennis W. Jansen, my advisor, and Dr. David A. Bessler, Dr. Hae-Shin Hwang, Dr. Hagen Kim, and Dr. Qi Li for their precious guidance and encouragement. I also wish to thank my friends and colleagues, Kyoung Soo Han, Raul Ibarra, Stefan Jacewits, Erasmus Kersting, Joseph Kim, Hyoung Il Lee, and Danillo Trupkin for their helpful discussions throughout various presentations and seminars.

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CHAPTER I

INTRODUCTION

The on-going economic downturn followed by the financial turmoil triggered by the fallout in the mortgage market has let economists keep their eyes on issues about the relationship between monetary policy and asset prices. "How much the monetary policy shocks have an effect on housing price since 2000" has been a controversial issue among monetary economists. Based on identified BVAR, various techniques such as impulse response, historical decomposition, and conditional forecasting are involved in exploring the relationship between monetary policies and housing prices. In addition, the relationship between monetary policy and stock prices is explored as an extension of Dupor and Conley (2004). They argue that Fed might respond more swiftly and boldly to non-fundamental stock price movements given its' first concern, i.e. low and stable inflation, is achieved. Their argument is reevaluated in a newly built-in non-linear setup. Finally, the identification of the dominant cause of apparent change in the Fed behavior, between structural change and nonlinearity, is explored.

In chapter II, multi-step ahead forecast performances among SS BAVR, standard BVAR and ML VAR (estimated by maximum likelihood) are compared based on rolling window scheme.

This dissertation follows the style of Journal of Monetary Economics.

Specifically upon the usual squared error loss methodology, the forecasting performances in comparison with the benchmark, ML VAR are evaluated in each step-ahead. In addition, equal predictive ability tests following Giacomini and White (2006) verify that the SS BVAR is superior in forecasting performance especially in the long-horizons. This is consistent with the intuition that SS BVAR indicates as Villani (2008) points out the advantage of SS BVAR exploiting prior information of steady state components in the long-horizon forecasting stages.

In chapter III, alternative identification schemes involving the housing sector are explored through two different approaches, as well as Wold causal ordering (Choleski decomposition). Not only economic theory-based approach which includes extensions of Gordon and Leeper (1994) and Sims and Zha (2006) but also algorithms of inductive causations using the directed acyclic graphs (DAGs) are used in specification of the housing sector. The impulse responses of the housing price and investment to the monetary policy shock illustrate that the response of the housing sector is smaller in magnitude, less significant, and relatively shorter in all four alternative specifications when compared to the Choleski case. Also historical decomposition and conditional forecasting analysis are involved to revisit the relationship between monetary policy and housing price. In those counterfactual simulations, the housing price cannot be well explained without feeding housing price's own shocks. Also generated forecasts of housing price since 2000 conditional on actual paths of real GDP (y), inflation (p), money demand (m), 30-yr. mortgage rate ($mor30$) and FFRs (i) do not generate the sharp increase and sudden drop of housing price since 2003. Feeding simulated FFRs based on

Taylor rule instead of actual FFRs change little the conditional forecasting results. Based on the findings across more generalized identifications, it is conjectured that there has been more uncertainty than we may know about the relationship between monetary policy and housing market as Mishkin (2007) and Kohn (2007) point out. Thus, the views that the housing price boom and fallout has been driven or fortified by the monetary policy shocks since 2000 are called in to question. Rather, institutional factors such as the securitization of mortgage market or lax loan standard creating easy access to risky credit are presumably deeply related with the housing price episode since 2000 as DiMartino and Duca (2007) and Fisher (2008) point out.

In chapter IV, Dupor and Conley (2004)'s argument that the Fed might be more successful in raising (or lowering) the interest rate responding to non-fundamental stock price movements in low inflation era is reexamined based on a newly built nonlinear set-up. Specifically, since early 1990s, the so-called low inflation era, the Fed has more easily or boldly responded to non-fundamental stock price movements given its first concern, i.e., low and stable inflation is achieved. After replicating Dupor and Conley (2004)'s estimation results using same methodology such as forward-looking interest rate rule estimated by GMM, it is found that their linear estimation results are not robust to different breakpoints. An alternative way of relaxing this problem is introducing nonlinear forward-looking interest rate rule introducing "series method" which allows carrying over the original GMM specification. After establishing the nonlinear model, we revisit Dupor and Conley (2004)'s argument with the interesting hypothesis that between nonlinearity and structural change which is the dominant cause of the apparent changes in Fed behavior. Test results under extended instrumental variables (IVs) following Andrews (1999) indicate that both nonlinearity and structural change matter in explaining the Fed's behavior in response to inflation and stock variable movements. Given the existence of a structural change, the inflation coefficient's movements show that the Fed has responded to expected inflation pressure nonlinearly across sub-periods, while the stock price gap coefficient's show an explicit break around the early 1990s, confirming Dupor and Conley (2004)'s finding.

CHAPTER II

BAYESIAN VAR AND FORECASTING PERFORMANCES

2.1. Basic Idea and Minnesota Prior

The overall scheme using Bayesian VAR can be summarized in Figure 2.1. Using prior, i.e. useful, information and likelihood functions which come from restriction on the error term, we can derive full conditional posterior density through the application of Bayes' theorem. The driven full conditional posterior density, however, is not usually solved analytically. Thus, a numerical method called 'Gibbs sampling' is involved.

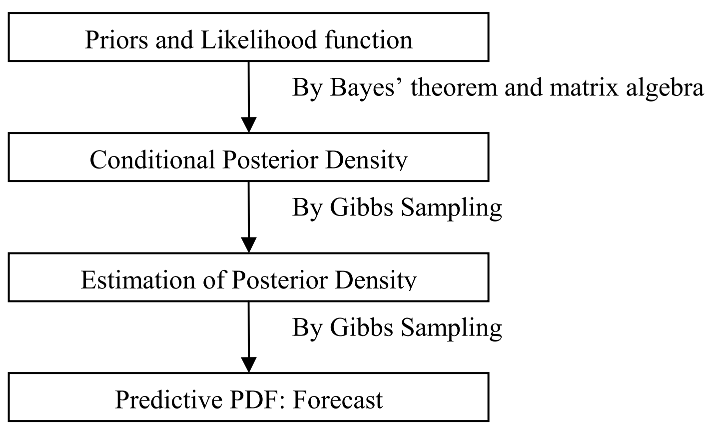

Fig. 2.1. Overall scheme of Bayesian VAR

The essential element in the Bayesian approach is Bayes' theorem which can be illustrated by Zellner (1971):

$$p(y,\theta) = p(y \mid \theta)p(\theta) = p(\theta \mid y)p(y)$$

And thus,

$$p(\theta \mid y) = \frac{p(\theta)p(y \mid \theta)}{p(y)}$$

where $p(y,\theta)$ is joint probability density function (pdf) for a random observation vector y and a parameter vector θ. With $p(y) \neq 0$ we can write this last expression as follows:

$$\begin{aligned} p(\theta \mid y) &\propto p(\theta)p(y \mid \theta) \\ &\propto prior\ \ pdf \times likelihood\ \ function \end{aligned}$$

where $\propto$ denotes proportionality, and $p(\theta|y)$ is the posterior pdf for the parameter vector θ given sample information y.

The Minnesota (or Litterman) prior has been the most popular and powerful prior used in Bayesian VAR framework. In brief, this prior is informative on all the dynamic coefficients while deterministic components are non-informative. It can be explained following Litterman (1986) and Bauwens et. al. (1999). We can write the VAR system as follows:

$$\Pi(L)x_t = \Phi + \varepsilon_t$$

$$\Pi(L) = I_p - \Pi_1 L - \Pi_2 L^2 - \cdots - \Pi_k L^k$$

where $x_t, \Phi,$ *and* ε_t are $p\times 1$ matrices where p is number of endogenous variables. The Minnesota prior expectation says that the VAR system consists of p random walks. That is, the prior mean Π_1 is I_p (identity matrix with p dimension) and prior means of Π_i ($i \geq$ 2) are all zero matrices with p dimension. The prior covariance matrix of all the parameters in the Π_i ($i \geq 1$) matrices are diagonal and some decreasing patterns are seen as follows: The standard deviation of diagonal element of Π_1 is the fixed value of λ, the standard deviation of dynamic coefficient of own variable's lag i is λ/i, the standard deviation of dynamic coefficients of the lags of every other variable is $\lambda\theta\sigma_k / i\sigma_j$, i.e. the standard deviation of lag i of the variable x_j in equation k. The parameter θ ($0 \leq \theta \leq 1$) makes the standard deviation ($\lambda\theta / i$) to be tighter around zero when compared to own variable's (λ/i). This incorporates the idea that the lags of x_j (the other variable) are more likely to have zero coefficients than the lags of x_k (same variable). The ratio σ_k / σ_j of the standard deviations of the error terms is a way to account for the difference in the variability of the different variables. So following the example equation illustrates the above discussions about the prior means and standard deviations which are given in parentheses.

$$x_{1,t} = \underset{(1,\,\lambda)}{\alpha_{11}} x_{1,t-1} + \underset{(0,\,\lambda/2)}{\alpha_{12}} x_{1,t-2} + \underset{(0,\,\theta\lambda\sigma_1/\sigma_2)}{\beta_{11}} x_{2,t-1} + \underset{(0,\,\theta\lambda\sigma_1/2\sigma_2)}{\beta_{12}} x_{2,t-2} + \varepsilon_{1,t}$$

2.2 Steady State Bayesian VAR

Like the Minnesota prior, most available priors of VARs focus solely on the dynamic coefficients but are largely non-informative on the deterministic component of the model.[1] A non-informative prior on the deterministic part of the process might have an undesirable consequence when we conduct the forecast on the grounds that the long run forecasts from stationary VARs converge to an unconditional mean or steady state of the process as pointed out by Villani (2008).

[1] For the detailed discussions about standard Bayesian VAR, see Ciccarelli and Rubucci (2003) and, for the discussions about various priors, see Rao and Karlsson (1997).

In reality, it is feasible to obtain prior information about the steady state usually from the long period of sample mean and standard deviation. For example, we already know that the steady state or very long-term mean of US real output is around 3%. Also, forecast of inflation under an explicit inflation target undertaken by central banks can be a good example associated with the priors about the deterministic component in the process. So, using the steady state form of the Bayesian VAR (SS BVAR) equipped with informative prior on the deterministic component can alleviate the forecasting difficulty in the Bayesian VAR setup.

Now, the basic model of SS BVAR will be illustrated following the notation and illustration of Villani (2008). The advantage of using the steady state (or mean-adjusted) form of VAR is that the unconditional mean of the process is directly specified by Ψ as $E_0(x_t) = \Psi d_t$ while it is nonlinear function of parameter $\Pi(L)$ and Φ in the standard VAR form. The basic system can be written as follow:

$$\Pi(L)x_t = \Phi d_t + \varepsilon_t \quad ==> \quad \Pi(L)(x_t - \Psi d_t) = \varepsilon_t$$

where x_t is p-dimensional vector of time series at time t, d_t is q-dimensional vector of deterministic trends or other exogenous variables (in this dissertation, I keep $d_t = 1$), $\Pi(L) = I_p - \Pi_1 L - \Pi_2 L^2 - \cdots - \Pi_k L^k$, $\Pi = (\Pi_1,...,\Pi_k)'$, and $\varepsilon_t \sim N_p(0,\Sigma)$ which is assumed to be independence between time periods. Bayesian inference requires a prior distribution on $\Sigma, \Pi,$ and Ψ , i.e. all parameter vectors. The standard prior information on Σ and Π is used. For steady state prior, the available steady state information largely depending on both the basic macro-economic theories and sample information is involved. Further assumptions about the prior independence between Π and Ψ are made following Villani (2008). Those priors can be summarized as follows:

$p(\Sigma) \propto |\Sigma|^{-(p+1)/2}$: Jeffrey's prior

$vec\Pi \sim N_{kp^2}(\theta_\Pi, \Omega_\Pi)$: Multivariate normal distribution which is Minnesota Prior.

$vec\Psi \sim N_{pq}(\theta_\Psi, \Omega_\Psi)$: Multivariate normal distribution which is available from steady state (or sample data) information.

The joint posterior distribution of SS BVAR is intractable. Instead, each full conditional posterior distribution is feasible. Once we obtain the full conditional posterior distributions, we can construct joint posterior density using a numerical method called Gibbs sampling. The specific steps of derivation of each conditional posterior based on Villani (2008) are attached in Appendix A. In addition, in Appendix B contains simplified generated-data illustration to show that even with mild informative priors on steady state, the accuracy of estimation results are considerably enhanced. The summary of main results of posteriors follows:

Full conditional posterior of Σ **:** $p(\Sigma \mid \Pi, \Psi, I_t) \sim IW(E'E, T)$

where *IW* denotes "*inverted Wishart*" form and $E = \lfloor \Pi(L)(x_t - \Psi d_t) \rfloor$ ($T\times p$), $\lfloor \ \rfloor$ denotes the usual rearrangement of data vectors into a matrix for the whole sample and I_t denotes available data at time *t*.

Full conditional posterior of Π**:** $p(vec\Pi \mid \Sigma, \Psi, I_t) \sim N_{kp^2}(\bar{\theta}_\Pi, \bar{\Omega}_\Pi)$

where $\bar{\Omega}_\Pi^{-1} = \Sigma^{-1} \otimes X_\Psi^{'} X_\Psi + \Omega_\Pi^{-1}$, $\bar{\theta}_\Pi = \bar{\Omega}_\Pi [vec(X_\Psi^{'} Y_\Psi \Sigma^{-1}) + \Omega_\Pi^{-1}\theta_\Pi]$, $Y_\Psi = \lfloor x_t - \Psi d_t \rfloor$ ($T \times p$), and $X_\Psi = \lfloor x_{t-1} - \Psi d_{t-1}, ..., x_{t-k} - \Psi d_{t-k} \rfloor$ ($T \times p*k$) matrices respectively.

Full conditional posterior of $\bar{\Psi}$**:** $p(vec\Psi \mid \Sigma, \Pi, I_t) \sim N_{pq}(\bar{\theta}_\Psi, \bar{\Omega}_\Psi)$

where $\bar{\Omega}_\Psi^{-1} = U'(D'D \otimes \Sigma^{-1})U + \Omega_\Psi^{-1}$, $\bar{\theta}_\Psi = \bar{\Omega}_\Psi [U' vec(\Sigma^{-1} Y' D) + \Omega_\Psi^{-1}\theta_\Psi]$, $Y = \lfloor \Pi(L) x_t \rfloor$ ($T \times p$), $U' = (I_{pq}, I_q \otimes \Pi_1^{'}, ..., I_q \otimes \Pi_k^{'})$ $(p^2 k \times p^2 k)$, and $D = \lfloor d_t, -d_{t-1}, ..., -d_{t-k} \rfloor$ $(T \times (k+1)q)$ matrices respectively.

2.3. Gibbs Sampling

As previously discussed, the joint distribution of the parameters cannot be solved analytically, i.e. it is only possible to handle conditional joint distribution. The technique used to derive from this conditional distribution to joint distribution is Gibbs sampling. The key feature of this algorithm is that samples are only drawn from the full conditional distributions $\pi(x_i \mid x_{-i})$. The realizations of the draw finally converge to the joint distribution[2]. The Gibbs sampling algorithm is one of Markov Chain Monte Carlo's (MCMC) simulation methods. Its algorithm can be summarized as follows:

(Step1) Pick arbitrary starting values $(\Sigma^0, \Pi^0, \Psi^0)$

(Step2) Successively make random drawings from the full conditional distributions as follows:

[2] For further discussion, see Smith and Roberts (1993).

$\Sigma^1 \quad from \quad p(\Sigma \mid \Pi^0, \Psi^0, I_T);$

$\Pi^1 \quad from \quad p(\Pi \mid \Sigma^1, \Psi^0, I_T);$

$\Psi^1 \quad from \quad p(\Psi \mid \Sigma^1, \Pi^1, I_T);$

$\Sigma^2 \quad from \quad p(\Sigma \mid \Pi^1, \Psi^1, I_T);$

$\Pi^2 \quad from \quad p(\Pi \mid \Sigma^2, \Psi^1, I_T);$

$\Psi^2 \quad from \quad p(\Psi \mid \Sigma^2, \Pi^2, I_T);$

(Step3) Iterate this scan to produce a sequence $(\Sigma, \Pi, \Psi)^0$, $(\Sigma, \Pi, \Psi)^1$, $(\Sigma, \Pi, \Psi)^2$,…, $(\Sigma, \Pi, \Psi)^k$ where k can be 1,000 or 5,000 or 10,000 etc.

2.4 Data, Priors and Posteriors

The eight endogenous variable system of Jarocinski and Smets (2008) are used, with one exception of the 30-yr. mortgage rate while they use the spread between 10-yr government bond rate and FFR. The reasons for using mortgage rate are straightforward. First, the mortgage rate is presumably more closely and directly related with the housing market. Second, the spread could be redundant in the alternative identification designs when using FFR as short-term interest rate in spread calculation. Also, a more extended dataset of OFHEO's (Office of Federal Housing Enterprise Oversight) housing price index[3], which starts from 1975Q1, is used. Another popular home price index is 'S&P/Case-Shiller' which is available since 1987Q1 and used by Jarocinski and Smets

[3] The OFHEO index is based on a repeated-sales method which measures average price changes in repeat sales on the same properties. This information is obtained by reviewing mortgage loans which have been purchased by Fannie Mae and Freddie Mac.

(2008). Table 2.1 displays the endogenous variables, their compiling, and their abbreviated expressions which will be used hereafter.

Table 2.1
Data description: Endogenous variable

Abbreviation	Description	Compiling
y_t	Log difference of real GDP	$\Delta\log(GDP_t)$
p_t	Log difference of real GDP deflator	$\Delta\log(deflator_t)$
hi_t	Log ratio of residential investment over GDP	$\log(hi_t/GDP_t)$
hp_t	Difference between log difference of OFHEO Index and p_t (The 'real (or relative) housing price')	$\Delta\log(OFHEO_t) - \Delta\log(deflator_t)$
cp_t	Log difference of Dow-Jones Spot Average of commodity price	$\Delta\log(commodity\ price_t)$
i_t	Federal Funds rate	-
$mor30_t$	30-yr Mortgage Rate	-
m_t	Log difference of M2 money stock	$\Delta\log(M2_t)$

Note: 1) Monthly data are converted into quarterly average basis. 2) All growth rates are on an annual basis, i.e. four-quarter growth rate. 3) Data source is St. Louis Fed except housing price (OFHEO) and commodity price (Global Financial Data, acronym: _DJSD).

The Minnesota priors on first own lag variables are all set at zero except three level variables, i.e. *hi*, *i*, and *mor30,* to which 0.9 are assigned. Note that the original Minnesota prior for the means of first own lag variable is one due to the assumption that the processes are random walk. However, this random walk prior is inconsistent with the mean-adjusted set-up where the stationarity of the processes is assumed.

Table 2.2
Prior and posterior means and standard deviations of the steady states

	y_t	p_t	hi_t	hp_t	cp_t	i_t	$mor30_t$	m_t
Prior Mean	3.00	3.00	-3.00	0.00	3.00	6.00	8.00	6.00
Std.	1.00	1.00	1.00	2.00	2.50	2.00	2.50	1.50
Posterior Mean	2.96	3.12	-3.07	2.25	3.03	5.52	8.34	5.55
Std.	0.27	0.48	0.03	0.61	1.70	0.86	0.88	0.79

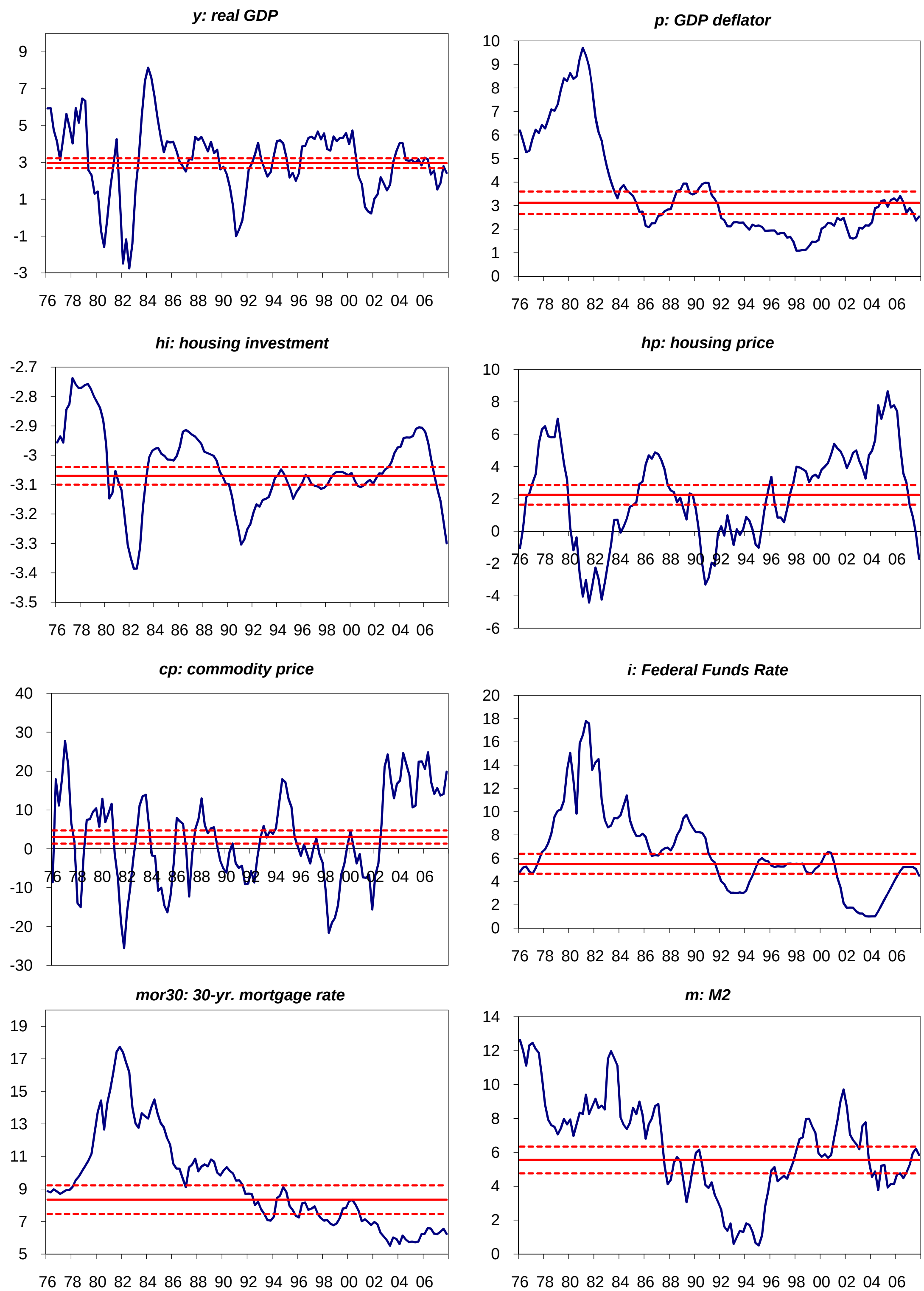

Fig. 2.2. Data plots and their posterior means and standard deviations

Table 2.2 illustrates the priors and posteriors of means and standard deviations of the steady state. The priors are formed based on common knowledge about the U.S. economy. First, we believe that the steady state real GDP growth rate is around 3% and steady state inflation is 2.5~3.5%, from which we pick 3.5% since the dataset includes the high inflation era of the 1970s. Using the Fisher equation and quantity equation of money, we set the priors for nominal interest rate (*i*) and money growth rate (*m*). The prior for *mor30* is set by the sum of short-term interest rate (*i*) plus some premiums reflecting time preference and credit risk. For *hi*, *hp*, and *cp* we use realized information from the quite long-term dataset. Overall, the mean of posteriors are located around priors and the standard deviations show relatively tighter range than the priors. Figure 2.2 displays the plots of the endogenous variables and their posterior (estimated) means and standard deviations.

2.5 Out-of-Sample Predictive Ability Tests

The forecasting performance comparisons among three VARs - ML VAR, which is the benchmark, the standard BVAR, and SS BVAR - are conducted. Multi step-ahead out-of-sample forecasts based on rolling window estimation scheme are produced. The estimation windows, forecasting horizons, and *h* step-ahead forecasts are illustrated in Table 2.3. The first estimation window is from 1976Q1 to 1995Q4, and the corresponding forecasting horizon is from 1996Q1 to 2000Q4 which produces 1~20 step-ahead forecasts. The next estimation window is from 1976Q2 to 1996Q1, and the corresponding one is 1996Q2 to 2001Q1 which also produces 1~20 step-ahead forecasts.

Subsequently, this type of rolling window forecast is iterated until the estimation window can be from 1987Q4 to 2007Q3 and the corresponding forecasting horizon is 2007Q4 which produces one step-ahead forecast.

Table 2.3
Estimation windows, forecasting horizons, and step-ahead forecasts

	Estimation Windows	Forecasting Horizons	*h*-step ahead
1	76Q1 ~ 95Q4	96Q1 ~ 2000Q4	1~20
2	76Q2 ~ 96Q1	96Q2 ~ 2001Q1	1~20
3	76Q3 ~ 96Q2	96Q3 ~ 2001Q2	1~20
⋮	⋮	⋮	⋮
28	82Q4 ~ 2002Q3	2002Q4 ~ 2007Q3	1~20
29	83Q1 ~ 2002Q4	2003Q1 ~ 2007Q4	1~20
30	83Q2 ~ 2003Q1	2003Q2 ~ 2007Q4	1~19
31	83Q3 ~ 2003Q2	2003Q3 ~ 2007Q4	1~18
⋮	⋮	⋮	⋮
47	87Q3 ~ 2007Q2	2007Q3 ~ 2007Q4	1~2
48	87Q4 ~ 2007Q3	2007Q4	1

So, for one step-ahead forecast, 48 observations are obtained; for two step-ahead, 47; for three step-ahead, 46; and for twenty step-ahead forecast, 29 observations are obtained. For the two BVARs, the forecasts are predictive means among 1000 realizations. The sequence of out-of-sample forecasts is evaluated by mean squared error loss using the following equation:

$$mean\ squared\ error\ loss = \frac{\sum_{i=1}^{n} forecast\ error_i^2}{n}$$

where *forecast error = actual realization – forecast* and *n* is the observations of the forecasts in each step ahead.

Plots of mean squared error loss are displayed in Figure 2.3. Overall, the mean squared losses of SS BVAR are much less than those of benchmark ML VAR. When compared to the standard BVAR, the performance of SS BVAR is clearly better in *p*, *hi*, *i* and *m* while in the case of *mor30* and *hp* the performance of the standard BVAR is better. For the *y* and *cp,* it is unclear from the plots.

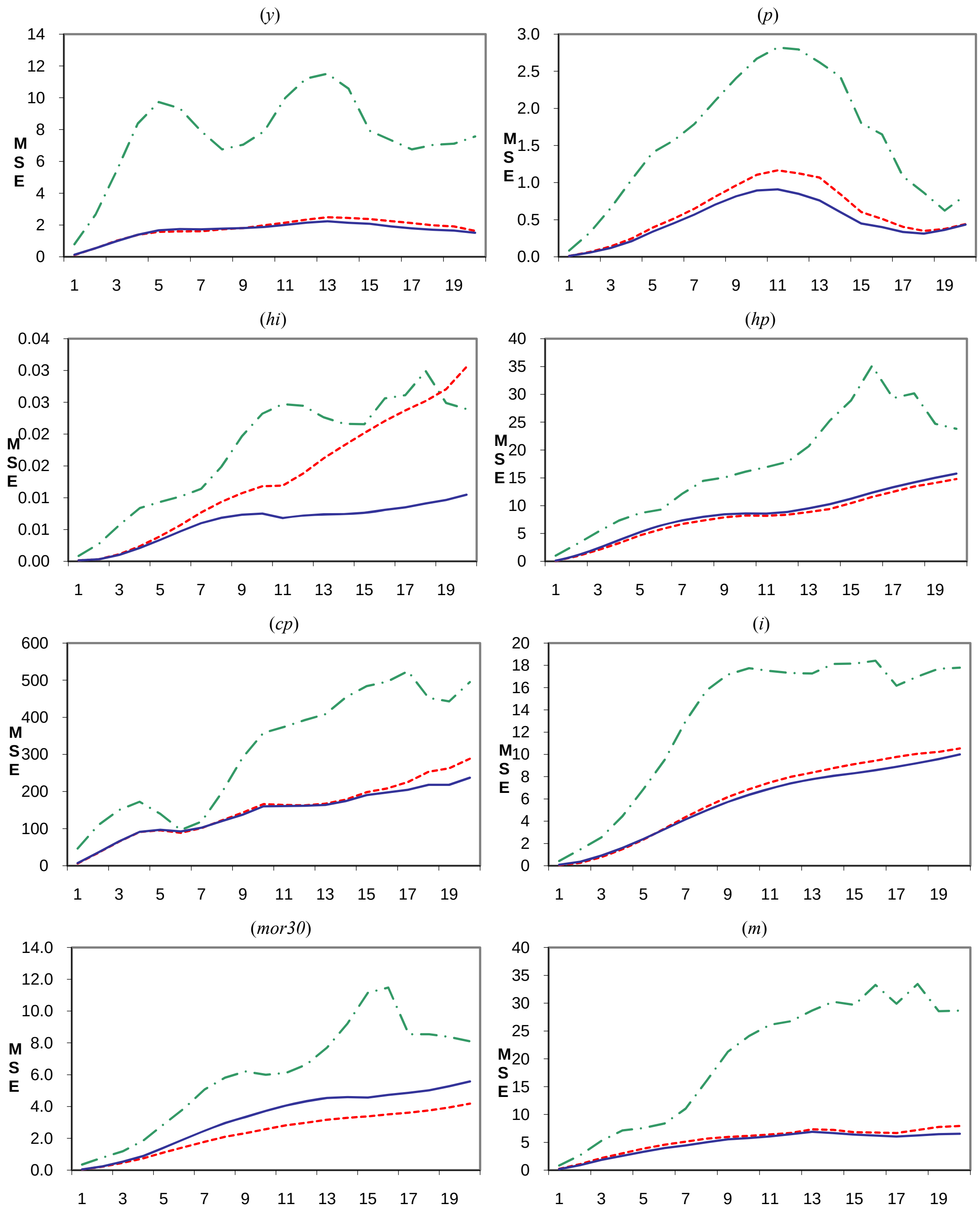

Fig. 2.3. Out-of-sample evaluation of point forecasts (predictive mean). Each sub-graph displays the average squared errors loss for each step-ahead forecast.

The relative ratios of squared error losses when compared to the benchmark ML VAR are shown in Table 2.4. Therefore, the less the ratio, the better the forecasting performance. For all variables except *hp* and *mor30*, the ratios of SS BVAR are less than those of the standard BVAR.

Following Giacomini and White (2006), predictive ability tests were conducted. Their method is applicable to the multi step-ahead forecast, unlike Clark and McCraken's (2001) which focuses solely on one step-ahead case. Giacomini and White (2006) exploit the fact that difference series between the losses in each one step-ahead forecast is a martingale difference sequence (MDS) for a given σ-field F_t. To put it more specifically, for a given loss function and σ-field F_t, null hypothesis of equal predictive ability of forecast *f* and *g* for the target date τ conditional on σ-field F_t can be written as equation (1).

$$H_0 : E[(Y_{t+\tau} - \hat{f}_{t,m})^2 - (Y_{t+\tau} - \hat{g}_{t,m})^2 | F_t] = E[\Delta L_{m,t+\tau} | F_t] = 0 \qquad (1)$$

where $Y_{t+\tau}$ is actual realization, $(Y_{t+\tau} - \hat{f}_{t,m})^2$ and $(Y_{t+\tau} - \hat{g}_{t,m})^2$ are model specific losses, and *m* is the index of estimation window. When τ =1, the null hypothesis (1) claims that $\{\Delta L_{m,t}, F_t\}$ is a MDS. Then the conditional moment restriction, $E[\Delta L_{m,t+1} | F_t] = 0$ is "equivalent to stating that $E[h_t \Delta L_{m,t+1}] = 0$ for all F_t-measurable function h_t" as Giacomini and White (2006) point out. Hereafter, the 2×1 F_t-measurable function $h_t = (1, \Delta L_t)'$ is used following their practical application. Using the MDS property

$E[h_t \Delta L_{t+1}] = 0$, a Wald-type test statistic based on standard asymptotic normality argumentation can be constructed, which is displayed in equation (2).

Table 2.4
Ratio of relative squared error losses in each step-ahead forecast

		Forecast Horizon: Quarters Ahead									
		1(48)	*2(47)*	*3(46)*	*4(45)*	*5(44)*	*6(43)*	*7(42)*	*8(41)*	*9(40)*	*10(39)*
y	*SS BVAR*	0.166	0.203	0.182	0.166	0.171	0.186	0.217	0.262	0.255	0.237
	S BVAR	0.146	0.203	0.187	0.165	0.162	0.171	0.203	0.255	0.256	0.250
p	*SS BVAR*	0.119	0.173	0.180	0.201	0.241	0.287	0.318	0.334	0.339	0.335
	S BVAR	0.137	0.201	0.212	0.237	0.279	0.328	0.362	0.385	0.399	0.413
hi	*SS BVAR*	0.185	0.117	0.182	0.252	0.362	0.464	0.528	0.460	0.373	0.323
	S BVAR	0.166	0.117	0.198	0.283	0.422	0.560	0.674	0.628	0.545	0.508
hp	*SS BVAR*	0.117	0.347	0.443	0.516	0.608	0.691	0.605	0.553	0.561	0.534
	S BVAR	0.068	0.298	0.381	0.446	0.537	0.618	0.552	0.508	0.525	0.511
cp	*SS BVAR*	0.150	0.326	0.436	0.530	0.690	0.960	0.860	0.607	0.471	0.447
	S BVAR	0.130	0.317	0.433	0.527	0.680	0.922	0.853	0.616	0.490	0.464
i	*SS BVAR*	0.191	0.243	0.357	0.357	0.348	0.346	0.320	0.316	0.334	0.359
	S BVAR	0.104	0.176	0.301	0.331	0.340	0.352	0.336	0.337	0.359	0.387
mor30	*SS BVAR*	0.105	0.295	0.439	0.477	0.488	0.500	0.486	0.508	0.536	0.621
	S BVAR	0.094	0.275	0.383	0.395	0.385	0.372	0.351	0.359	0.374	0.429
m	*SS BVAR*	0.202	0.328	0.349	0.357	0.433	0.471	0.401	0.312	0.259	0.239
	S BVAR	0.264	0.396	0.411	0.421	0.512	0.543	0.462	0.352	0.280	0.255
		Forecast Horizon: Quarters Ahead									
		11(38)	*12(37)*	*13(36)*	*14(35)*	*15(34)*	*16(33)*	*17(32)*	*18(31)*	*19(30)*	*20(29)*
y	*SS BVAR*	0.200	0.191	0.194	0.202	0.262	0.260	0.264	0.242	0.231	0.199
	S BVAR	0.215	0.208	0.216	0.231	0.299	0.305	0.313	0.282	0.268	0.215
p	*SS BVAR*	0.322	0.304	0.290	0.248	0.249	0.242	0.308	0.361	0.584	0.522
	S BVAR	0.413	0.402	0.407	0.348	0.335	0.309	0.372	0.405	0.604	0.532
hi	*SS BVAR*	0.275	0.293	0.327	0.343	0.354	0.316	0.325	0.304	0.388	0.438
	S BVAR	0.481	0.565	0.714	0.842	0.936	0.861	0.908	0.842	1.087	1.278
hp	*SS BVAR*	0.506	0.497	0.461	0.406	0.389	0.351	0.454	0.470	0.607	0.661
	S BVAR	0.482	0.468	0.428	0.371	0.362	0.329	0.426	0.446	0.570	0.620
cp	*SS BVAR*	0.429	0.411	0.400	0.383	0.393	0.398	0.390	0.481	0.492	0.479
	S BVAR	0.438	0.414	0.409	0.393	0.409	0.420	0.430	0.560	0.592	0.583
i	*SS BVAR*	0.396	0.428	0.450	0.445	0.457	0.466	0.550	0.543	0.541	0.562
	S BVAR	0.427	0.462	0.485	0.483	0.502	0.512	0.605	0.592	0.578	0.592
mor30	*SS BVAR*	0.664	0.650	0.589	0.498	0.409	0.412	0.569	0.587	0.630	0.689
	S BVAR	0.460	0.448	0.411	0.357	0.302	0.306	0.423	0.439	0.471	0.516
m	*SS BVAR*	0.231	0.241	0.239	0.220	0.215	0.186	0.201	0.186	0.226	0.228
	S BVAR	0.245	0.250	0.256	0.239	0.229	0.203	0.222	0.215	0.271	0.277

Note: 1) Benchmark is maximum likelihood VAR forecast. That is, two BVARs' squared error losses are divided by those of maximum likelihood VARs' in each horizon. 2) S BVAR stands for standard Bayesian VAR. 3) The number of observations is given in parentheses.

$$T^h_{m,n} = n(n^{-1}\sum_{t=m}^{T-1} h_t \Delta L_{m,t+1})'\hat{\Omega}_n^{-1}(n^{-1}\sum_{t=m}^{T-1} h_t \Delta L_{m,t+1}) = n\,\overline{Z}'_{m,n}\,\hat{\Omega}_n^{-1}\,\overline{Z}_{m,n} \tag{2}$$

where $\overline{Z}_{m,n} \equiv n^{-1}\sum_{t=m}^{T-1} Z_{m,t+1}$, $Z_{m,t+1} \equiv h_t \Delta L_{m,t+1}$, $\hat{\Omega}_n \equiv n^{-1}\sum_{t=m}^{T-1} Z_{m,t+1} \times Z'_{m,t+1}$ is a consistently estimated covariance matrix, and T is the total sample size. We reject the null hypothesis of equal conditional predictive ability whenever $T^h_{m,n} > \chi^2_{2,1-\alpha}$, where $\chi^2_{2,1-\alpha}$ is the (1 – α) quantiles of a χ^2 distribution with two degree of freedom. For a forecast horizon $\tau > 1$, the null hypothesis (equation (1)) implies that "for all F_t-measurable function h_t, the sequence $\{h_t \Delta L_{m,t+\tau}\}$ is finitely correlated, which implies that we only need to consider the correlations among the multi step-ahead forecasts, so that $\text{cov}(h_t \Delta L_{m,t+\tau}, h_{t-j}\Delta L_{t+\tau-j}) = 0$ for all $j \geq \tau$" as Giacomini and White (2006) point out. Using this feature, we can construct the following multi step-ahead test statistic in equation (3):

$$T^h_{m,n,\tau} = n(n^{-1}\sum_{t=m}^{T-\tau} h_t \Delta L_{m,t+\tau})'\tilde{\Omega}_n^{-1}(n^{-1}\sum_{t=m}^{T-\tau} h_t \Delta L_{m,t+\tau}) = n\,\overline{Z}''_{m,n}\,\tilde{\Omega}_n^{-1}\,\overline{Z}_{m,n} \tag{3}$$

where $\overline{Z}_{m,n} \equiv n^{-1}\sum_{t=m}^{T-\tau} Z_{m,t+\tau}$, $Z_{m,t+\tau} \equiv h_t \Delta L_{m,t+\tau}$, and $\tilde{\Omega}_n \equiv n^{-1}\sum_{t=m}^{T-\tau} Z_{m,t+\tau} \times Z'_{m,t+\tau} +$ $n^{-1}\sum_{j=1}^{\tau-1} w_{n,j} \times \sum_{t=m+j}^{T-\tau}[Z_{m,t+\tau}Z'_{m,t+\tau-j} + Z_{m,t+\tau-j}Z'_{m,t+\tau}]$, where $w_{n,j}$ is a weight function such that $w_{n,j} \to 1$ as n $\to \infty$ for each j = 1, …, τ – 1. Like one step-ahead case, we reject the null hypothesis of equal predictive ability whenever $T^h_{m,n,\tau} > \chi^2_{2,1-\alpha}$. The equal predictive ability tests with 95% significant level are displayed in Table 2.5.[4]

[4] I use the code provided in the author's webpage http://www.econ.ucla.edu/giacomin/.

Table 2.5
Equal predictive ability tests (*p*-values)

		Forecast Horizon: Quarters Ahead									
		1(47)	*2(46)*	*3(45)*	*4(44)*	*5(43)*	*6(42)*	*7(41)*	*8(40)*	*9(39)*	*10(38)*
y	*SS vs. ML*	0.069	0.524*	0.272*	0.147*	0.256*	0.293*	0.010	0.006	0.009	0.044
	S vs. ML	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.006	0.035
	SS vs. S	(0.001)	(0.000)	0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0.010	0.035
p	*SS vs. ML*	0.008	0.018	0.052	0.104*	0.142*	0.120*	0.027	0.002	0.001	0.001
	S vs. ML	0.001	0.003	0.005	0.001	0.010	0.017	0.019	0.011	0.000	0.003
	SS vs. S	0.001	0.002	0.002	0.000	0.006	0.015	0.019	0.017	0.003	0.024
hi	*SS vs. ML*	0.042	0.883*	0.027	0.005	0.000	0.000	0.012	0.070*	0.123*	0.072
	S vs. ML	0.000	0.004	0.013	0.056	0.042	0.164*	0.141*	0.099	0.072	0.047
	SS vs. S	(0.000)	(0.003)	0.004	0.029	0.054	0.197*	0.149*	0.084	0.045	0.007
hp	*SS vs. ML*	0.000	0.103	0.092	0.093	0.062	0.026	0.016	0.013	0.014	0.044
	S vs. ML	0.002	0.012	0.113*	0.148*	0.210*	0.220*	0.175*	0.075	0.046	0.034
	SS vs. S	(0.003)	(0.029)	(0.151*)	(0.110*)	(0.146*)	(0.209*)	(0.213*)	(0.100*)	(0.075)	(0.061)
cp	*SS vs. ML*	0.232*	0.115*	0.055*	0.041	0.027	0.152*	0.183*	0.007	0.305*	0.037
	S vs. ML	0.002	0.001	0.022	0.140*	0.045	0.008	0.020	0.091	0.105*	0.000
	SS vs. S	(0.002)	(0.002)	(0.025)	(0.153*)	(0.059)	(0.014)	(0.007)	0.131*	0.064	0.000
i	*SS vs. ML*	0.001	0.030	0.032	0.007	0.005	0.000	0.000	0.005	0.016	0.024
	S vs. ML	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SS vs. S	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	0.000	0.000	0.000	0.000	0.000
mor30	*SS vs. ML*	0.000	0.031	0.012	0.010	0.009	0.005	0.002	0.002	0.007	0.041
	S vs. ML	0.001	0.009	0.038	0.009	0.004	0.001	0.000	0.000	0.001	0.002
	SS vs. S	(0.001)	(0.005)	(0.021)	(0.002)	(0.004)	(0.003)	(0.000)	(0.000)	(0.000)	(0.002)
m	*SS vs. ML*	0.003	0.001	0.002	0.003	0.001	0.006	0.095	0.241*	0.345*	0.011
	S vs. ML	0.009	0.027	0.003	0.002	0.000	0.109*	0.205*	0.098	0.024	0.001
	SS vs. S	0.004	0.013	0.004	0.003	0.000	0.098	0.146*	0.067	0.018	0.001

		Forecast Horizon: Quarters Ahead									
		11(37)	*12(36)*	*13(35)*	*14(34)*	*15(33)*	*16(32)*	*17(31)*	*18(30)*	*19(29)*	*20(28)*
y	*SS vs. ML*	0.029	0.000	0.001	0.007	0.019	0.000	0.017	0.005	0.010	0.030
	S vs. ML	0.023	0.010	0.000	0.011	0.001	0.002	0.014	0.029	0.092*	0.072
	SS vs. S	0.023	0.009	0.000	0.008	0.000	0.001	0.007	0.019	0.080	0.082
p	*SS vs. ML*	0.000	0.000	0.000	0.001	0.017	0.013	0.001	0.000	0.036	0.149*
	S vs. ML	0.036	0.114*	0.138*	0.115*	0.131*	0.127*	0.027	0.011	0.166*	0.057
	SS vs. S	0.066	0.113*	0.144*	0.107*	0.130*	0.166*	0.052	0.007	0.128*	0.032
hi	*SS vs. ML*	0.044	0.065	0.018	0.002	0.000	0.000	0.000	0.000	0.000	0.000
	S vs. ML	0.028	0.010	0.295*	0.066	0.010	0.053	0.123*	0.003	(0.002)	(0.000)
	SS vs. S	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002
hp	*SS vs. ML*	0.083	0.098	0.120*	0.065	0.050	0.011	0.021	0.013	0.047	0.057
	S vs. ML	0.015	0.038	0.083	0.082	0.064	0.098	0.000	0.004	0.000	0.010
	SS vs. S	(0.049)	(0.026)	(0.084)	(0.087)	(0.074)	(0.110*)	(0.000)	(0.007)	(0.000)	(0.006)
cp	*SS vs. ML*	0.000	0.000	0.001	0.000	0.000	0.000	0.021	0.068	0.046	0.012
	S vs. ML	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.001	0.006
	SS vs. S	0.000	0.001	0.004	0.000	0.000	0.000	0.000	0.000	0.004	0.004
i	*SS vs. ML*	0.041	0.078	0.145*	0.154*	0.087	0.009	0.000	0.006	0.119*	0.010
	S vs. ML	0.006	0.019	0.018	0.014	0.025	0.035	0.048	0.000	0.000	0.000
	SS vs. S	0.005	0.009	0.008	0.023	0.034	0.020	0.014	0.000	0.000	0.000
mor30	*SS vs. ML*	0.084	0.123*	0.075	0.133*	0.147*	0.185*	0.266*	0.182*	0.113*	0.113*
	S vs. ML	0.027	0.093	0.076	0.080	0.114*	0.166*	0.042	0.166*	0.279*	0.334*
	SS vs. S	(0.136*)	(0.145*)	(0.087)	(0.050)	(0.090)	(0.066)	(0.089)	(0.048)	(0.021)	(0.002)
m	*SS vs. ML*	0.290*	0.193*	0.201*	0.100*	0.084	0.077	0.042	0.008	0.006	0.002
	S vs. ML	0.001	0.021	0.143*	0.228*	0.110*	0.000	0.000	0.000	0.000	0.000
	SS vs. S	0.001	0.030	0.152*	0.228*	0.114*	0.000	0.000	0.000	0.000	0.000

Note: 1) SS stands for steady state Bayesian VAR, S stands for standard Bayesian VAR, ML stands for maximum likelihood VAR. 2) * implies that the null hypothesis of equal predictive ability is not rejected at 90% significant level. 3) The parentheses denote that the standard Bayesian VAR's forecasts outperform to steady state Bayesian VAR in *SS vs. S* line, and for the case of *S vs. ML* in *hi* line, the maximum likelihood VAR's forecasts outperform to standard Bayesian VAR.

One observation which must be used in constructing of $h_t = (1, \Delta L_t)'$ is lost in each step-ahead stage. Overall, in most horizons, the equal predictive ability between both Bayesian predictions and benchmark ML's is rejected. Interestingly, the two Bayesian VAR's performance is similar under ten step-ahead cases while for the beyond horizons the SS BVAR outperforms, which is consistent with the intuition that SS BVAR indicates.

CHAPTER III

MONETARY POLICY AND HOUSING PRICE

3.1. Introduction

The on-going economic downturn, followed by financial turmoil triggered by fallout in the sub-prime mortgage market, has allowed economists to keep their eyes on issues about how the Fed should respond to housing prices, as well as the huge impact of the housing sector on real economy as we have seen since 2005. Especially in regards to the relationship between housing price and monetary policy, there has not been much research, while there has comparatively been a considerable amount for the relationship between monetary policy and real GDP or sometimes stock prices.

Taylor (2007) shows that the prolonged period of low interest rates has substantially contributed to the upward swing in housing price from 2003 through 2005 using the counterfactual scenario of Federal Funds Rates (FFRs) based on the Taylor rule, with a comparison to the actual movements of FFRs. Also, Jarocinski and Smets (2008) show that the FFRs is the most important factor accounting for the development of housing prices of the period using Bayesian VAR. In contrast, Mishkin (2007) demonstrates that what we know about the relationship between housing price and monetary policy is limited due to uncertainty caused by an unclear house-related monetary transmission mechanism. More recently, Kohn (2007) says that as more thorough research is being completed, the causes of the swing in housing price seem to be less consequences of monetary policy. Rather, he says it is a result of “the emotions of excessive optimism followed by fear experienced every so often in the marketplace through the ages…”.

In this chapter, the role of monetary policy in the housing market in the U.S. from the mid-1970s to date is examined using the identified steady state Bayesian vector autoregressive (SS BVAR) model. The mid 1970s is the starting point of housing price data which constitutes the longest one for the U.S. Their eight endogenous variables system and similar BVAR methodology are borrowed, but more generalized identification designs concerning the relationship between monetary policy and housing price are investigated. The alternative identification schemes are explored mainly focusing on the specifications of the housing sector in addition to the Wold causal ordering (Choleski decomposition) which Jarocinski and Smets (2008) use. The more general identifications relaxed from Choleski one are composed of two different approaches: economic theory-based and inductive causation using the directed acyclic graphs (DAGs). The first approach is based on economic theory about the relationship between housing sector and other macroeconomic variables. I insert housing sector specifications following Kearl (1979) into previous macroeconomic setups of Gordon and Leeper (1994) and Sims and Zha (2006). The second is somewhat statistical method called “directed acyclic graphs” (DAGs) which was explored by Hoover (2005) and Bessler and Lee (2002). The impulse response of housing price and investment to the monetary policy shock illustrates that the response of the housing sector is smaller in magnitude, less significant, and relatively shorter in all four alternative specifications when compared to the Choleski case. Also, the issue is revisited through historical decomposition which can clearly demonstrate how much each structural shock can contribute to the upward swing and sharp drop of housing prices since 2000. In this counterfactual simulation, the housing price cannot be well explained without feeding housing price's own shock. The housing investment movements can be relatively well accounted for by housing price shock and other macro variables without feeding its own shock. Forecasts for housing price since 2000, conditional on the assumption that we know various macroeconomic variables such as the actual paths of real GDP (*y*), inflation (*p*), money demand (*m*), 30-yr. mortgage rate (*mor30*) and actual or simulated FFRs by Taylor rule since 2000, were generated. These experiments verify that the forecasted housing price developments cannot pick up the run-up around 2005 and also indicate similar movements across actual and simulated FFRs based on the Taylor rule.

Based on the findings across more generalized identifications, it is conjectured that there has been more uncertainty than what we may know about the housing market as Mishkin (2007) and Kohn (2007) point out. Thus, the view that the housing price boom and fallout has been driven or fortified by monetary policy shocks since 2000 is called in to question. Rather, institutional factors such as securitization of the mortgage market or lax loan standards igniting easy access to risky credit[5] are presumably deeply related with the housing price episode since 2000.

In section 3.1, the alternative identification designs involving housing sectors are explored. In section 3.2, the impulse response analysis focusing on the monetary policy shock is conducted and the magnitudes and significance of housing sectors for all

[5] For detailed developments of sub-prime mortgage crisis, see DiMartino and Duca (2007).

identifications are compared. In section 3.3, the historical decomposition analysis focusing on the housing market is investigated. In section 3.4, the conditional forecasts of housing price following Waggoner and Zha (1999) are experimented. Finally, concluding remarks are drawn in section 3.5.

3.2 Identification Design Involving Housing Sector

The Wold causal ordering of Jarocinski and Smets (2008) for the housing sector identification can be summarized as follows. The variables are separated into three blocks: real sector (y and p), housing sector (hi and hp), and financial sector (cp, i, $spread$ and m). The spread between 10-yr. government bond rate and FFRs is used, and the ordering is from real sector to the financial sector, i.e. $y \rightarrow p \rightarrow hi \rightarrow hp \rightarrow cp \rightarrow i \rightarrow spread \rightarrow m$. This identification can be expressed by the contemporaneous matrix as in equation (4).

$$\begin{pmatrix} a_1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ a_2 & a_3 & 0 & 0 & 0 & 0 & 0 & 0 \\ a_4 & a_5 & a_6 & 0 & 0 & 0 & 0 & 0 \\ a_7 & a_8 & a_9 & a_{10} & 0 & 0 & 0 & 0 \\ a_{11} & a_{12} & a_{13} & a_{14} & a_{15} & 0 & 0 & 0 \\ a_{16} & a_{17} & a_{18} & a_{19} & a_{20} & a_{21} & 0 & 0 \\ a_{22} & a_{23} & a_{24} & a_{25} & a_{26} & a_{27} & a_{28} & 0 \\ a_{29} & a_{30} & a_{31} & a_{32} & a_{33} & a_{34} & a_{35} & a_{36} \end{pmatrix} \begin{bmatrix} y \\ p \\ hi \\ hp \\ cp \\ i \\ spread \\ m \end{bmatrix} \qquad (4)$$

The recursive structure which represents single straight ordering might not be realistic since the economic structure is not always consistent with that causal stream. So alternatively, the identification issues are explored in two different ways. First, the non-recursive structure based on economic theory, which has been explored since Bernanke

(1986) and Sims (1986) proposals, is explored. In this chapter, focus is kept on so-called "short-run restriction" on the contemporaneous matrix. The "long-run restriction" which usually exploits a characteristic of monetary neutrality in the long-run can also be an alternative identification[6]. Another is based on algorithms of inductive causations, which are called 'directed acyclic graphs' (DAGs). Hoover (2005) and Kim Leatham and Bessler (2007) illustrate and show how this method can be applied in the VAR setup.

3.2.1 Economic Theory Based Approach

First, the economic theory-based structure is discussed. Based on the research of Bernanke (1986) and Sims (1986), Sims (1992) tries to interpret and solve the so-called 'liquidity puzzle' (m (money) ↑ → i ↑) and 'price puzzle' (i ↑ (or m ↓) → p ↑). For the former, Sims (1992) conjectures that the monetary aggregate innovations reflect not only monetary policy shocks but also monetary demand shocks and suggest the system should involve the variable representing monetary policy shock such as FFRs and other variables representing monetary demand shock such as monetary aggregates. For the latter, Sims (1992) conjectures that some parts of innovations in interest rates are systematic responses to structural shocks generating inflationary pressure. Thus, after including some variables representing inflationary pressures such as commodity price index in the monetary reaction function, this problem can be resolved. This type of identification is also applied in the small open economy frame. Cushman and Zha (1997)

[6] For further discussion, see Blanchard and Quah (1989).

and Kim (1999) try to identify the monetary policy shocks based on short-run restriction for various countries.

Now, two identification designs are introduced based on the economic theory-based approach. These two designs were actually adopted with the augmentation of housing sector specifications. The first, from Gordon and Leeper (1994), introduces simultaneous interaction of supply and demand in federal funds markets. The endogenous variables are separated into two sectors: the money market sector, and the financial and goods market sector. The money demand usually has zero restriction on the grounds that the money demanders can observe lots of information such as opportunity costs of money holding (i), price of goods (p) that they want to purchase and their wealth (y) when they make their demand decisions[7] where i denotes short-term interest rate (FFR or 1 month TB rate), p Consumer Price Index, y Industrial Production, and i_{10} 10-yr. TB rate. For the money supply sector, the 'timing issue' is crucial, i.e. they postulate that the Fed can contemporaneously observe innovations of m, i_{10}, and cp where m denotes money demand and cp commodity price index. Simultaneous equation system of the money market can be written as equation (5). The financial and goods market are determined recursively in the order of unemployment (u), output (y), the price level (p), long-term interest rate (i_{10}) and commodity prices (cp).

(i) Money market

Money demand: $m + a_1 i + a_2 p + a_3 y = e_d$

[7] Gordon and Leeper (1994) adopt the convention of eliminating long-term rates from the money demand specification.

Money supply: $i + a_4 m + a_5 i_{10} + a_6 cp = e_s$ (5)

(ii) Financial and goods markets: u, y, p, i_{10}, and cp

The whole discussion of Gordon and Leeper (1994)'s identification design can be expressed by the contemporaneous matrix in equation (6).

$$\begin{pmatrix} 1 & a_4 & 0 & 0 & 0 & a_5 & a_6 \\ a_1 & 1 & 0 & a_3 & a_2 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & a_7 & 1 & 0 & 0 & 0 \\ 0 & 0 & a_8 & a_9 & 1 & 0 & 0 \\ 0 & 0 & a_{10} & a_{11} & a_{12} & 1 & 0 \\ 0 & 0 & a_{13} & a_{14} & a_{15} & a_{16} & 1 \end{pmatrix} \begin{bmatrix} i\,(MS) \\ m\,(MD) \\ u \\ y \\ p \\ i_{10} \\ cp \end{bmatrix} \tag{6}$$

The second design is from Sims and Zha (2006) where they try to show that VAR-style identifying restrictions work well in identifying monetary policy shock using the DSGE model frame. Their identifying restrictions can be summarized as follows:

(i) Monetary policy makes interest rate respond to *m*, *cp*, and *Tbk* (bankruptcy filing).

(ii) Money demand behavior makes *m* respond to *y, p*, and *i*.

(iii) They limit contemporaneous impact of *i* (monetary policy) on the financial sector.

(iv) They place importance on *cp*: *cp* does immediately impact all variables except *m*. Also through *cp*, other variables can be contemporaneously related with *i* (monetary policy) indirectly.

(v) Good market: block upper triangular in the order of *Tbk, y, W, p,* and *Pim* where *W* denotes average hourly earning, *y* GNP, *p* GNP deflator, *Pim* Produces's Price Index.

The whole discussion of Sims and Zha (2006)'s identification design can be expressed by contemporaneous matrix in equation (7). What is done for our identification is adapting the Gordon and Leeper (1994) and Sims and Zha (2006) in the eight-variable system with the housing sector identification based on associated economic theory.

$$\begin{pmatrix} a_1 & a_2 & a_3 & a_4 & a_5 & a_6 & a_7 & a_8 \\ 0 & a_9 & a_{10} & 0 & a_{11} & 0 & a_{12} & 0 \\ a_{13} & a_{14} & a_{15} & 0 & 0 & 0 & 0 & a_{16} \\ a_{17} & 0 & 0 & a_{18} & a_{19} & a_{20} & a_{21} & a_{22} \\ a_{23} & 0 & 0 & 0 & a_{24} & a_{25} & a_{26} & a_{27} \\ a_{28} & 0 & 0 & 0 & 0 & a_{29} & a_{30} & a_{31} \\ a_{32} & 0 & 0 & 0 & 0 & 0 & a_{33} & a_{34} \\ a_{35} & 0 & 0 & 0 & 0 & 0 & 0 & a_{36} \end{pmatrix} \begin{bmatrix} cp \\ m(MD) \\ i(MS) \\ Pim \\ p \\ W \\ y \\ Tbk \end{bmatrix} \tag{7}$$

The research about non-recursive structures has been heavily focused on the mutual relationship between output movements and monetary policy. The non-recursive identification of housing sector, however, has not been explored much by economists in the VAR setup. So, Kearl's (1979) research is borrowed for this purpose. In his research Kearl (1979) derives housing price and housing investment as an implicit function of macro variables basically using 'Stock and Flow' model.[8] He separates the housing market into two distinctive ones: market of housing services (Flow) and market of housing stock (Stock). Each market can be explained by supply and demand as follows:

(Market for Housing Services)

Supply: $H_s^s = \alpha\overline{H}$ (8)

[8] Following Kearl (1979)'s framework McCarthy and Peach (2002) estimate housing price and investment equations in error-correction model.

Demand: $H_s^d = \phi(R, y, p, hh)$ (9)

The flow of services from the fixed housing stock is in-elastically supplied. (Equation (8)) Thus R (rent) is clearing housing services' market in equation (9), where R denotes the price of the services (rent), y income, p the index of prices of other commodities and hh household characteristics.

(Market for Housing Stock)

Supply: Fixed as $\overline{H}$ in the short period of time

Demand: Flexible depending on the variables

In equilibrium under the perfect market assumption, the R, marginal benefit of house-owner is equal to marginal cost of the asset (right-hand side of equation (10)) which comprises of δ (depreciation) plus r (real interest) minus $\dot{hp}^{\varepsilon}$ (anticipated relative price change, i.e. capital gain) proportional to the housing price.

$$R = hp * (\delta + r - \dot{hp}^{\varepsilon}) \tag{10}$$

So, Housing price is determinant, i.e., $hp = R/(\delta + r - \dot{hp}^{\varepsilon})$ given R is determined in the service market and $\delta + r - \dot{hp}^{\varepsilon}$ is exogenous under competitive conditions. Now, using equations (8) and (9), we can derive the relationship between housing price and housing stock:

$$\begin{aligned}\overline{H} &= \frac{1}{\alpha} H_s^s = \frac{1}{\alpha} H_s^d = \frac{1}{\alpha}\phi(R, y, p, hh) \\ &= \frac{1}{\alpha}\phi(hp * (\delta + r - \dot{hp}^{\varepsilon}), y, p, hh)\end{aligned}$$

Therefore, $hp = \varphi(\overline{H}, \delta + r - \dot{hp}^{\varepsilon}, y, p, hh)$ since $\delta + r - \dot{hp}^{\varepsilon}$ is given exogenously outside of the housing market. The relative housing price can be written as equation (11). Over a long period of time, $\overline{H}$ is not fixed so *hp* will be affected by construction activity (or housing investment).

$$hp / p = \psi(\overline{H}, \delta + r - \dot{hp}^{\varepsilon}, y, hh) \tag{11}$$

When the equation (11) is adapted in my eight variables' system, we can postulate that the relative housing price could react or depend on $\overline{H}$ (housing investment, *hi*), interest rate (*i* or *mor30*), income (*y*), and other unknown shocks (*hh*) such as households' preferences, institutional changes, etc.

Now, the effect of *hp* (housing price) on *hi* (housing investment) is examined. The hp^d (housing price of demand side) can be assumed to be independent of construction activity (i.e. $hp^d = \bar{hp}$) because, over a short period of time, the housing stock is negligibly affected by changes in construction. In contrast, the hp^s (housing price of supply side) regulates the supply flow of housing capital as this is the price at which builders can sell new units. That is, $hp^s = \eta(hi, c)$ where *hi* is the housing investment flow and *c* is vector of costs. Finally in equilibrium, $hp^s = \bar{hp}$ and thus it can be written as equation (12).

$$hi = \eta^{-1}(\bar{hp}, c) \tag{12}$$

Based on the equation (12), we can postulate that *hi* could react or depend on *hp* (housing price). It is further postulated that *y* and *p* can constitute *c* (vector of costs) as instruments of overall economic state. In addition, following the intuition of Sims and Zha (2006), it is further postulated that the *hp* and *hi* would fully respond to the *cp* whose market is open every day and circulates credible economic information. In the Gordon and Leeper (1994) application case this *cp*-related postulation is not carried over.

$$\begin{pmatrix} a_1 & 0 & 0 & 0 & 0 & a_2 & a_3 & a_4 \\ 0 & a_5 & a_6 & 0 & 0 & a_7 & a_8 & 0 \\ a_9 & a_{10} & a_{11} & 0 & 0 & 0 & 0 & a_{12} \\ 0 & 0 & a_{13} & a_{14} & a_{15} & a_{16} & 0 & a_{17} \\ 0 & 0 & 0 & a_{18} & a_{19} & a_{20} & a_{21} & 0 \\ 0 & 0 & 0 & 0 & 0 & a_{22} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & a_{23} & a_{24} & 0 \\ 0 & 0 & 0 & 0 & 0 & a_{25} & a_{26} & a_{27} \end{pmatrix} \begin{bmatrix} cp \\ m(MD) \\ i(MS) \\ hp \\ hi \\ y \\ p \\ mor30 \end{bmatrix} \tag{13}$$

(Simultaneous Equations System) (14)

$$\begin{aligned}
&a_1 cp_t + a_2 y_t + a_3 p_t + a_4 mor30_t = \varepsilon_t^{cp} \\
&a_5 m_t + a_6 i_t + a_7 y_t + a_8 p_t = \varepsilon_t^{m} \\
&a_9 cp_t + a_{10} m_t + a_{11} i_t + a_{12} mor30_t = \varepsilon_t^{i} \\
&a_{13} i_t + a_{14} hp_t + a_{15} hi_t + a_{16} y_t + a_{17} mor30_t = \varepsilon_t^{hp} \\
&a_{18} hp_t + a_{19} hi_t + a_{20} y_t + a_{21} p_t = \varepsilon_t^{hi} \\
&a_{22} y_t = \varepsilon_t^{y} \\
&a_{23} y_t + a_{24} p_t = \varepsilon_t^{p} \\
&a_{25} y_t + a_{26} p_t + a_{27} mor30_t = \varepsilon_t^{mor30}
\end{aligned}$$

Now, applying the Gordon and Leeper (1994) combined by housing sector specification into eight variables' system, equation (13) and (14) display the contemporaneous matrix and simultaneous equation system respectively. This is over-identification system with 27 unknown parameters; given 36 unknown parameters are the case of just-identified. The housing sector follows based on Kearl (1979). Money demand and supply follow the intuitions of Gordon and Leeper (1994). Finally, the rest of the economy is recursively determined in the ordering of *y*, *p, mor30,* and *cp*.[9]

[9] I keep the *cp* in first row of contemporaneous matrix for consistency with other identification schemes.

Equations (15) and (16) show the application results of Sims and Zha (2006) and housing sector specification. Actually, the money market and the housing sector are exactly the same as Gordon and Leeper (1994) except the role of the *cp,* where the *cp* can respond to all endogenous variables and the rest of the variables except *m* can react to the *cp*. This design is a just-identified case.

$$\begin{pmatrix} a_1 & a_2 & a_3 & a_4 & a_5 & a_6 & a_7 & a_8 \\ 0 & a_9 & a_{10} & 0 & 0 & a_{11} & a_{12} & 0 \\ a_{13} & a_{14} & a_{15} & 0 & 0 & 0 & 0 & a_{16} \\ a_{17} & 0 & a_{18} & a_{19} & a_{20} & a_{21} & 0 & a_{22} \\ a_{23} & 0 & 0 & a_{24} & a_{25} & a_{26} & a_{27} & 0 \\ a_{28} & 0 & 0 & 0 & 0 & a_{29} & 0 & 0 \\ a_{30} & 0 & 0 & 0 & 0 & a_{31} & a_{32} & 0 \\ a_{33} & 0 & 0 & 0 & 0 & a_{34} & a_{35} & a_{36} \end{pmatrix} \begin{bmatrix} cp \\ m(MD) \\ i(MS) \\ hp \\ hi \\ y \\ p \\ mor30 \end{bmatrix} \tag{15}$$

(Simultaneous Equations System) (16)

$$a_1 cp_t + a_2 m_t + a_3 i_t + a_4 hp_t + a_5 hi_t + a_6 y_t + a_7 p_t + a_8 mor30_t = \varepsilon_t^{cp}$$
$$a_9 m_t + a_{10} i_t + a_{11} y_t + a_{12} p_t = \varepsilon_t^{m}$$
$$a_{13} cp_t + a_{14} m_t + a_{15} i_t + a_{16} mor30_t = \varepsilon_t^{i}$$
$$a_{17} cp_t + a_{18} i_t + a_{19} hp_t + a_{20} hi_t + a_{21} y_t + a_{22} mor30_t = \varepsilon_t^{hp}$$
$$a_{23} cp_t + a_{24} hp_t + a_{25} hi_t + a_{26} y_t + a_{27} p_t = \varepsilon_t^{hi}$$
$$a_{28} cp_t + a_{29} y_t = \varepsilon_t^{y}$$
$$a_{30} cp_t + a_{31} y_t + a_{32} p_t = \varepsilon_t^{p}$$
$$a_{33} cp_t + a_{34} y_t + a_{35} p_t + a_{36} mor30_t = \varepsilon_t^{mor30}$$

3.2.2 Algorithms of Inductive Causations: DAGs

Using the directed acyclic graphs (DAGs), structural shock is identified according to Hoover (2005) and Kim, Leatham and Bessler (2007).[10] The DAGs are pictures summarizing the causal flow among a set of innovations. The DAGs methodology derives the contemporaneous causal flow among data based on the

[10] For the further discussion about DAGs, see Spirtes, Glymour, and Schienes (2000).

algorithms of inductive causation. There are edges (or arrows) which represent such flows. The graph X → Y (directed graph) denotes that variable X causes variable Y. A line between two variables, say X − Y (undirected graph) indicates that X and Y are related but we cannot tell if X causes Y or Y causes X. No edges between X and Y (X Y) indicates (conditional) independence between two variables.

In the DAGs, there are three key conceptions. First is a "causal chain". Suppose that A → B → C (i.e. A causes B causes C). Here, A and C would be dependent unconditionally; however, they would be independent conditional on B. In this case the B is said to "screen A from C". Second is a "causal fork". Suppose that A ← B → C. Then, similar logic can be applied, i.e. A and C would be dependent unconditionally; however, conditional on B, they would be independent. In this case, the B is said to be the "common cause of A and C". Third is a "causal inverted fork" which is rather different from the previous two conceptions. Suppose that A → B ← C. Here we have B as a common effect of A and C. The A and C will have no association (zero correlation if constrained to linear relationship); however, conditional on B, the association between A and C is non-zero, i.e. dependent. In this case, the B is called "unshielded collider" on the path ABC.

The causal search algorithms (TETRAD IV) have been developed and are publicly accessible on the web page (http://www.phil.cmu.edu/projects/tetrad/). Two algorithms used in my analysis are introduced, borrowing explanations and illustrations from Hoover (2005), Kim, Leatham and Bessler (2007) and built-in manuals of TETRAD IV program. The basic assumption for the continuous dataset is that the direct causal influence of any variable on any other is linear and that the distribution of each variable is normal. The first is PC algorithm which is most commonly used in the DAGs analysis. The implementation step can be summarized as follows:

(Step 1) Initially construct complete undirected causal link.

(Step 2) Test for unconditional correlation of each pair of variables. Eliminate the link whenever the absence of correlation cannot be rejected.

(Step 3) Adjacency Phase: removing links

Test for the correlation of each variable conditional on third or more variables. Remove the links (or edges) X − Y if some set S, such that X and Y is uncorrelated conditional on S, can be found.

(Step 4) Orientation Phase: adding orientations

(i) We use separating set (sep-set) to find unshielded collider, i.e., when we remove the edge between A and B in the triple A – B – C, using conditional correlation, we can infer the collider A → B ← C, because B was not conditioned to remove the edge between A and C. If B was the conditioning variable to remove the edge then we could have A → B → C or A ← B ← C or A ← B → C.

(ii) If there is a link A → B − C, then orient the second link toward C, i.e. A → B → C: causal chain.

(iii) If there is an undirected link A − B and directed path, starting at A through one or more other variables to B, then orient the undirected link as A → B.

Another algorithm is GES (Greedy Equivalence Search) which is based on Bayesian scoring function. The GES algorithm searches over classes of equivalent DAGs called “pattern”. The pattern is an equivalence class of an acyclic graph, which represents the set of edges that can be determined by the search, with as many of these edges oriented as possible using the available information. Kim, Leatham and Bessler (2007) illustrate the causal flows among macroeconomic variables including REITs return rate using this GES algorithm. The search is composed of two steps:

(Step 1) Forward Sweep

(i) Begin with independence graph.

(ii) Find edges if Bayesian posterior score (Bayesian Information Criteria: BIC) increases once added.

(iii) Orient edges using above PC orientation rules.

(Step 2) Backward Sweep

(i) Remove edges or reversing the orientation if such actions result in improvement in the Bayesian posterior score.

(ii) Once it gets to the point where there is no edge any more than once removed increases the score, the algorithm stops.

The reduced form residuals are used as input data. The DAGs from PC algorithm and from GES are shown in Figure 3.1 and Figure 3.2 respectively. Several interesting features come out when compared to the identifications of economic theory approaches. The most striking result is that the *cp* (commodity price) and *m* (money demand) are ranked as highest exogenous status unlike the cases of economic theoretic approaches.

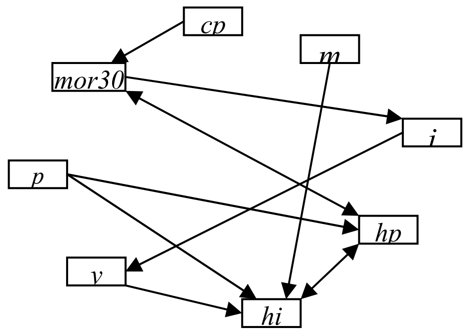

Fig. 3.1. DAGs from PC Algorithm

$$\begin{pmatrix} a_1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & a_2 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & a_3 & 0 & 0 & 0 & 0 & a_4 \\ 0 & 0 & 0 & a_5 & a_6 & 0 & a_7 & a_8 \\ 0 & a_9 & 0 & a_{10} & a_{11} & a_{12} & a_{13} & 0 \\ 0 & 0 & a_{14} & 0 & 0 & a_{15} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & a_{16} & 0 \\ a_{17} & 0 & 0 & a_{18} & 0 & 0 & 0 & a_{19} \end{pmatrix} \begin{bmatrix} cp \\ m(MD) \\ i(MS) \\ hp \\ hi \\ y \\ p \\ mor30 \end{bmatrix} \tag{17}$$

(Simultaneous Equations System) (18)

$$a_1 cp_t = \varepsilon_t^{cp}$$
$$a_2 m_t = \varepsilon_t^{m}$$
$$a_3 i_t + a_4 mor30_t = \varepsilon_t^{i}$$
$$a_5 hp_t + a_6 hi_t + a_7 p_t + a_8 mor30_t = \varepsilon_t^{hp}$$
$$a_9 m_t + a_{10} hp_t + a_{11} hi_t + a_{12} y_t + a_{13} p_t = \varepsilon_t^{hi}$$
$$a_{14} i_t + a_{15} y_t = \varepsilon_t^{y}$$
$$a_{16} p_t = \varepsilon_t^{p}$$
$$a_{17} cp_t + a_{18} hp_t + a_{19} mor30_t = \varepsilon_t^{mor30}$$

Housing price and investments reaction functions, however, are somewhat similar to the cases of economic theory-based approaches. Also, *i* (FFR) causes *y* (output growth) and *i* (FFR) reacts to *mor30* (30-yr. mortgage rates) in the DAGs from PC, while their relations are undirected in the DAGs from GES. There is double directed edge between *hp* (housing price) and *hi* (housing investment), which may appear due to failure of assumptions (e.g. relationship is non-linear, the population graph is cyclic, etc.) or indicate existence of latent variable between two variables. In the GES algorithm, three undirected edges are found as follows: *mor30* - *cp*, *mor30* - *i*, *y* - *i*. These undirected edges are consistent with eight possible directed causal relationships. Among them, *cp* → *mor30*, *mor30* → *i*, and *i* → *y* were chosen following the PC algorithm's result.

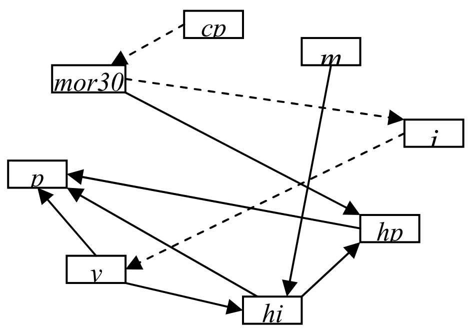

Fig. 3.2. DAGs from GES Algorithm

$$\begin{pmatrix} a_1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & a_2 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & a_3 & 0 & 0 & 0 & 0 & a_4 \\ 0 & 0 & 0 & a_5 & a_6 & 0 & 0 & a_7 \\ 0 & a_8 & 0 & 0 & a_9 & a_{10} & 0 & 0 \\ 0 & 0 & a_{11} & 0 & 0 & a_{12} & 0 & 0 \\ 0 & 0 & 0 & a_{13} & a_{14} & a_{15} & a_{16} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & a_{17} \end{pmatrix} \begin{bmatrix} cp \\ m(MD) \\ i(MS) \\ hp \\ hi \\ y \\ p \\ mor30 \end{bmatrix} \tag{19}$$

(Simultaneous Equations System) (20)

$$a_1 cp_t = \varepsilon_t^{cp}$$
$$a_2 m_t = \varepsilon_t^{m}$$
$$a_3 i_t + a_4 mor30_t = \varepsilon_t^{i}$$
$$a_5 hp_t + a_6 hi_t + a_7 mor30_t = \varepsilon_t^{hp}$$
$$a_8 m_t + a_9 hi_t + a_{10} y_t = \varepsilon_t^{hi}$$
$$a_{11} i_t + a_{12} y_t = \varepsilon_t^{y}$$
$$a_{13} hp + a_{14} hi_t + a_{15} y_t + a_{16} p_t = \varepsilon_t^{p}$$
$$a_{17} mor30_t = \varepsilon_t^{mor30}$$

3.2.3 Estimation of Contemporaneous Matrix

Identified contemporaneous matrices derived from both theory-based and statistical approaches are over-identified except in the Sims and Zha (2006) application. Those parameters of simultaneous equation system were estimated using the maximum likelihood method.[11] Following Enders (2003) and Hamilton (1994), the estimation steps can be summarized as follows. The reduced and structural form of our VAR can be represented as equation (21) and (22) respectively.

Reduced Form

$$Iy_t = \Pi_1 y_{t-1} + \Pi_2 y_{t-2} + \cdots + \Pi_k y_{t-k} + \varepsilon_t,\ \text{var}(\varepsilon_t) = \Sigma \tag{21}$$

Structural Form

$$By_t = B_1 y_{t-1} + B_2 y_{t-2} + \cdots + B_k y_{t-k} + e_t,\ \text{var}(e_t) = I_p \ \text{diagonal} \tag{22}$$

The linkages between two forms are $e_t = B\varepsilon_t$, $I = B\Sigma B'$ in residual relations. Basically, exploiting this relationship in the specific steps can be described as follows:

(Step 1) Estimate the reduced form VAR.
: The restrictions on B or $var(e_t)$ do not affect the estimation of VAR coefficients.

(Step 2) Obtain the reduced form variance/covariance matrix Σ (= $\hat{\Sigma}_U$ *Unrestricted*).
: The determinant of this matrix is an indicator of the overall fit of the model.

(Step 3) Restricting B will affect the estimate of Σ. Select the appropriate restrictions

[11] I use and adapt public software code called "Christopher Sims' Optimizer" (or 'csminwell' algorithm) which is based on the Broyden-Fletcher-Goldfarb-Shannon update of the Hessian matrix. In the earlier work of Blanchard and Watson (1986), they estimate it using instrumental variable method.

and maximize the likelihood function with respect to the free parameters of *B*.

- Log likelihood function of unrestricted form: $-\frac{T}{2}\ln|\Sigma|-\frac{1}{2}\sum_{t=1}^{T}\varepsilon_t'\Sigma^{-1}\varepsilon_t$
- Fix the values of ε_t with OLS estimators ($\hat{\varepsilon}_t$). Now use the relation $I = B\Sigma B'$
- Log likelihood function can be written as: $-\frac{T}{2}\ln\left|B^{-1}(B')^{-1}\right|-\frac{1}{2}\sum_{t=1}^{T}\hat{\varepsilon}_t'B'B\hat{\varepsilon}_t$
- Select the restrictions on *B* and maximize with respect to the remaining free parameters of *B*.

(Step 4) If the restriction is not binding, Σ_U and Σ_R ($=\hat{B}^{-1}(\hat{B}')^{-1}$ *Restricted*) will be equivalent. $\textit{Test statistic} = (T-k)*(\ln|\Sigma_R|-\ln|\Sigma_U|) \sim \chi^2(R)$, where k is the number of parameters estimated per equation and R is the number of over-identifying restrictions.

Estimation results of contemporaneous matrices in all identification schemes are displayed in Appendix C. The estimations for two DAGs are well done in view of over-identification test results displayed in Table 3.1 while the case of Gordon and Leeper (1994) application has very low *p*-value. Probably, it could not be a fair comparison because two DAGs innovations from reduced form are used to construct the causal flow, which can lead to closer correlations between covariance matrices of structural and reduced forms. Note that Sims and Zha (2006) plus housing sector cases is just-identified. Interestingly, most of the parameters from the DAGs are significant, while in the case of theory-based approaches, roughly half of the estimates are significant.

Table 3.1
LR Test for over-identification

	Chi-square test statistic	*p*-value
Gordon and Leeper (1994) plus housing sector	26.927 (9)	0.001
DAGs from PC algorithm	12.939 (17)	0.740
DAGs from GES algorithm	26.334 (19)	0.121

Note: The number of over-identifying restrictions is in parentheses.

3.3 Impulse Response Analysis

Once structural shocks are identified, one of the most popular analyses in VAR, i.e. the impulse response analysis, can be conducted. Using the relationship between reduced and structural form and moving average (MA) representation, we can write down each endogenous variable in the weighted average of each structural shock as follows:

$$
\begin{aligned}
y_t &= \sum_{i=0}^{\infty} \Phi_i \varepsilon_{t-i} \text{ , where } \Phi_0 = I_p \text{ and } \Phi_i = \sum_{j=0}^{i-1} \Pi_{i-j} \Phi_j \quad i = 1, 2, \cdots, k-1 \\
&= \sum_{i=0}^{\infty} \Phi_i B^{-1} e_{t-i} \text{ , given } \operatorname{var}(e_t) = I_p
\end{aligned}
$$

The impulse response in all five identifications such as Choleski, Gordon and Leeper plus housing sector (GL+, hereafter), Sims and Zha plus housing sector (SZ+, hereafter), DAGs from PC algorithm (PC, hereafter), and DAGs from GES algorithm (GES, hereafter) are examined. When focusing on the housing sector's response to the monetary policy shock, consistent and interesting results can be seen. In all identifications derived from both theory-based and statistical-based approaches, the responses of *hp* and *hi* are relatively smaller in magnitude, less significant, and shorter in response period when compared to the Choleski case. These results are illustrated in Figure 3.3. Also, Table 3.2 displays the peak magnitudes in responses which illustrate that the magnitudes of *hp* and *hi* in alternative identifications are roughly half of the Choleski case. For the four alternative identifications, the 68% probability bands include zeros or upper bands close to zero, which implies a less significant response from the housing sector. These estimation results are consistent with the views of Mishkin (2007) and Kohn (2007) who conjecture much uncertainty between housing sector and monetary policy. Figure 3.4 shows the impulse response of other variables except of the housing sector to monetary policy shock. The stylized facts are overall confirmed in all five identifications. That is, when *i* increases, *y* decreases, *p* decreases, *hi* and *hp* decrease, *cp* decreases and *mor30* increases. However, the money demand response is puzzling, and the *y* and *p*'s responses are somewhat ambiguous in the PC and GES cases.

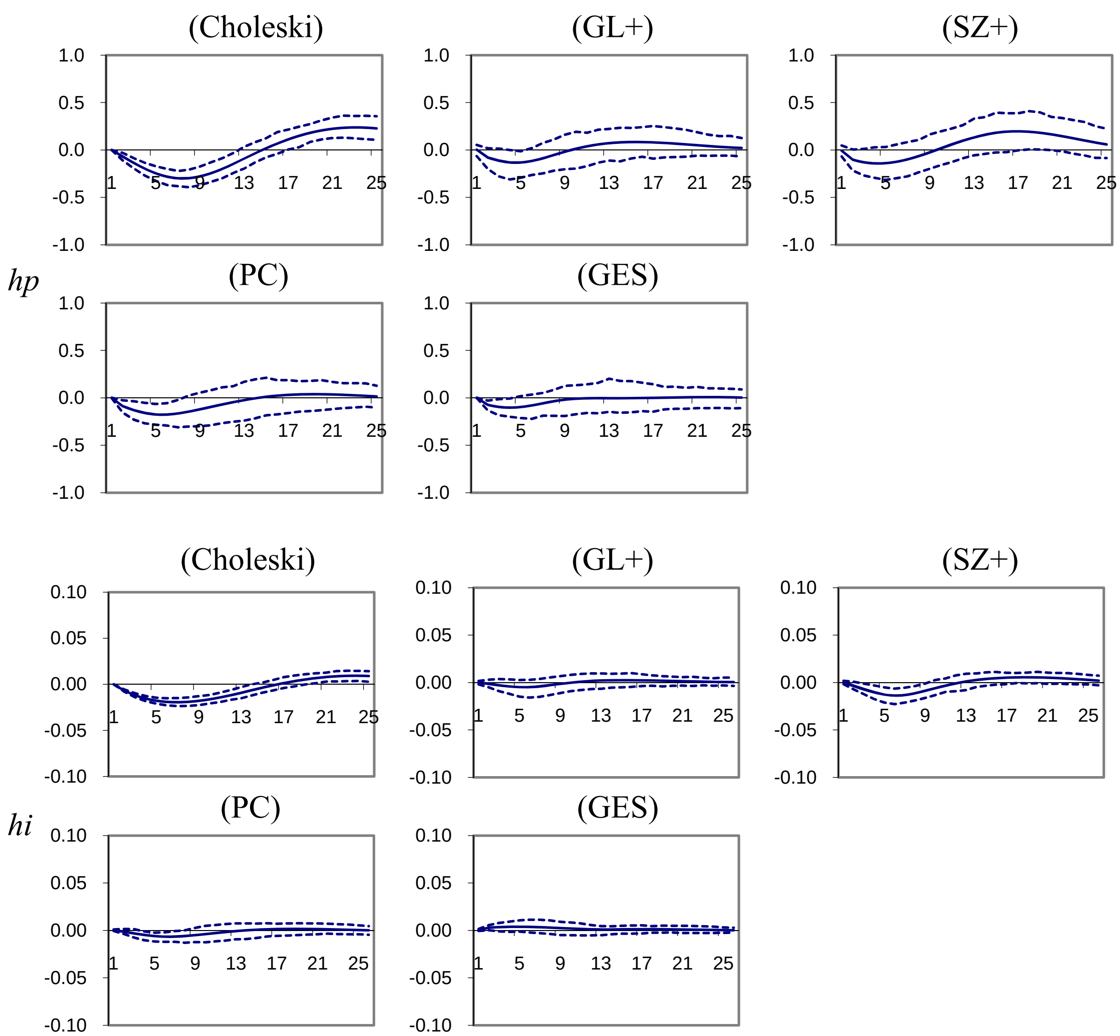

Fig. 3.3. Housing sector response to positive monetary policy shock. The solid lines represent average values and dotted lines represent 68% probability bands from 1000 realizations.

Table 3.2
Peak response of housing sector to monetary policy shock

	Choleski	GL+	SZ+	PC	GES
Housing Price (*hp*)	-0.2802	-0.1312	-0.1393	-0.1756	-0.1029
Housing Investment (*hi*)	-0.0194	-0.0049	-0.0137	-0.0065	-0.0002

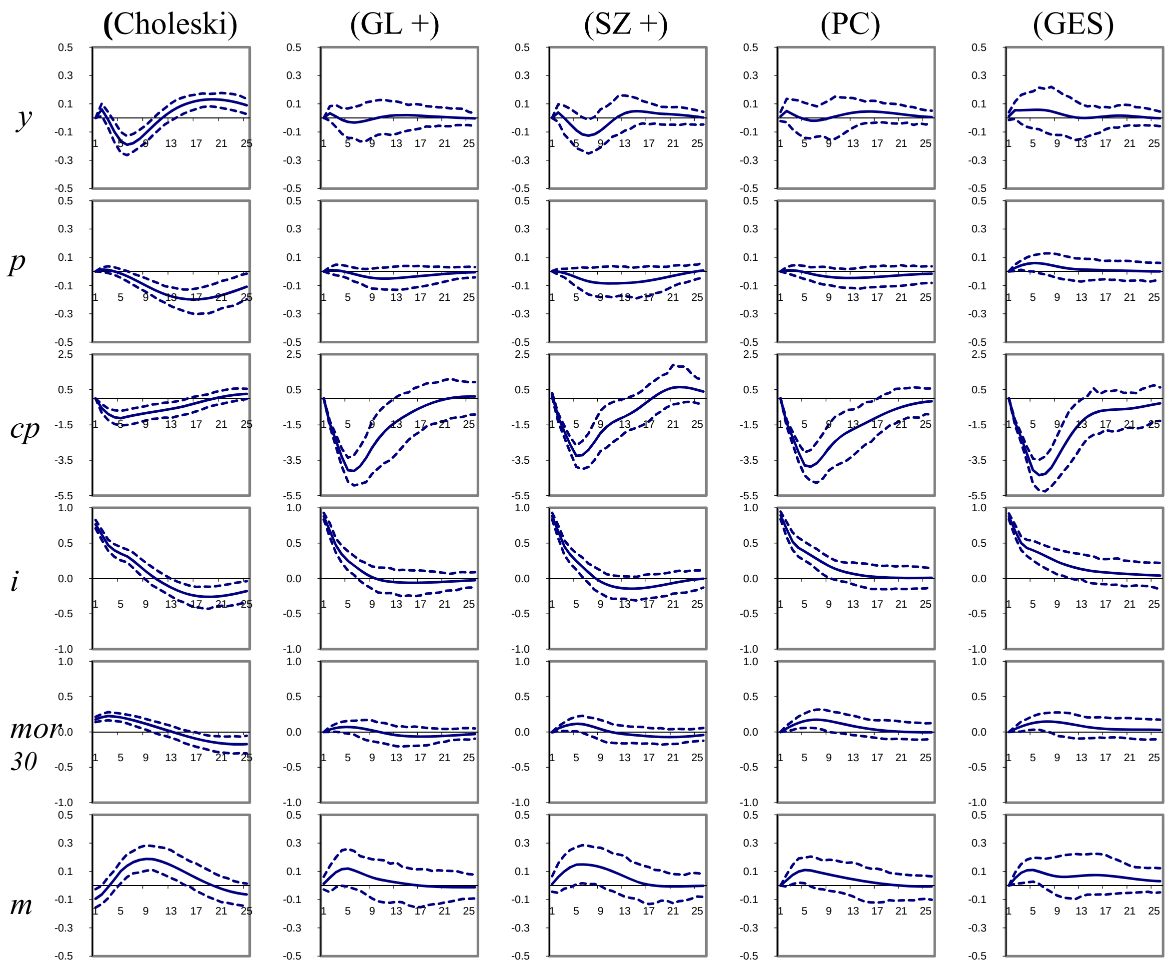

Fig. 3.4. Other variables' response to positive monetary policy shock. The solid lines represent average values and dotted lines represent 68% probability bands from 1000 realizations.

Additionally, the monetary policy shock's effect on other economic variables such as output and inflation are also smaller and less significant in all alternative identifications. Sims and Zha (2006) show that the monetary policy shock's effect on the output and other economic variables is relatively smaller than previously believed when applying their identification design. Another interesting result is the response of commodity price (*cp*). In GL+ to GES, the most significant and strong responses to monetary policy shock come from *cp*'s compared to the case of Choleski.

3.4 Historical Decomposition

The substantial uncertainty between monetary policy and housing price is also viewed from a different angle called historical decomposition analysis. This is a counterfactual method to show how the development of housing price would change when each identified shock is shut down while feeding all other shocks. Using this technique, the relative contribution of each historical shock to the housing price can be assessed. The basic methodology is relatively simple. Using the relationship between reduced and structural form, we can rewrite equation (22) as follows:

$$y_t = B^{-1}B_1 y_{t-1} + B^{-1}B_2 y_{t-2} + \cdots + B^{-1}B_k y_{t-k} + B^{-1}e_t \text{, given } \operatorname{var}(e_t) = I_p .$$

Then, this equation can be decomposed into the base projection (forecast) given information at time *t-1* ($B^{-1}B_1 y_{t-1} + B^{-1}B_2 y_{t-2} + \cdots + B^{-1}B_k y_{t-k}$) and sum of (weighted) contribution of the structural innovations to the actual data ($B^{-1}e_t^*$).

Here, the period of 2000 to date is examined, i.e. 2000 Q1 to 2007 Q4. Figure 3.5 and 3.6 display the historical decomposition of housing price. As can be easily verified from the plots, all other variables' structural shocks cannot account for a considerable portion of the development of housing price, especially the high peak around 2005.[12] These results lead to the conjecture that housing price shocks such as institutional factors (regulation/deregulation), lax loan standards, preferences of consumers, etc., are essential in accounting for the development of housing price. Furthermore, it supports the view that the run-up of housing price since 2000 is "bubble" as Shiller (2005) and Case and Shiller (2003) argue, in the sense that the housing price developments cannot be well explained by economic fundamentals.[13]

When shutting down the other shocks, the counterfactual movements of *hp* can follow the real data developments quite well in all identification designs as shown in Figure 3.6.

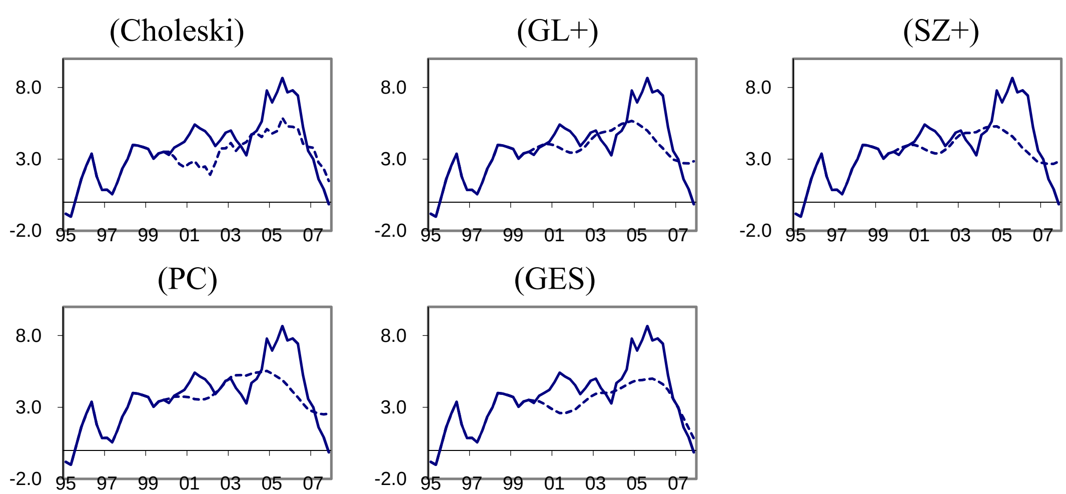

Fig. 3.5. Counterfactual when shutting down housing price shock. The solid lines represent actual data and the dotted lines represent the mean value of counterfactual from 1000 realizations when shutting down the structural shock of housing price.

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[12] The time series of structural shocks is included in Appendix E.

[13] In contrast, McCarthy and Peach (2004) illustrate that the housing price developments since 2000 can be well explained when using more economically refined housing price series.

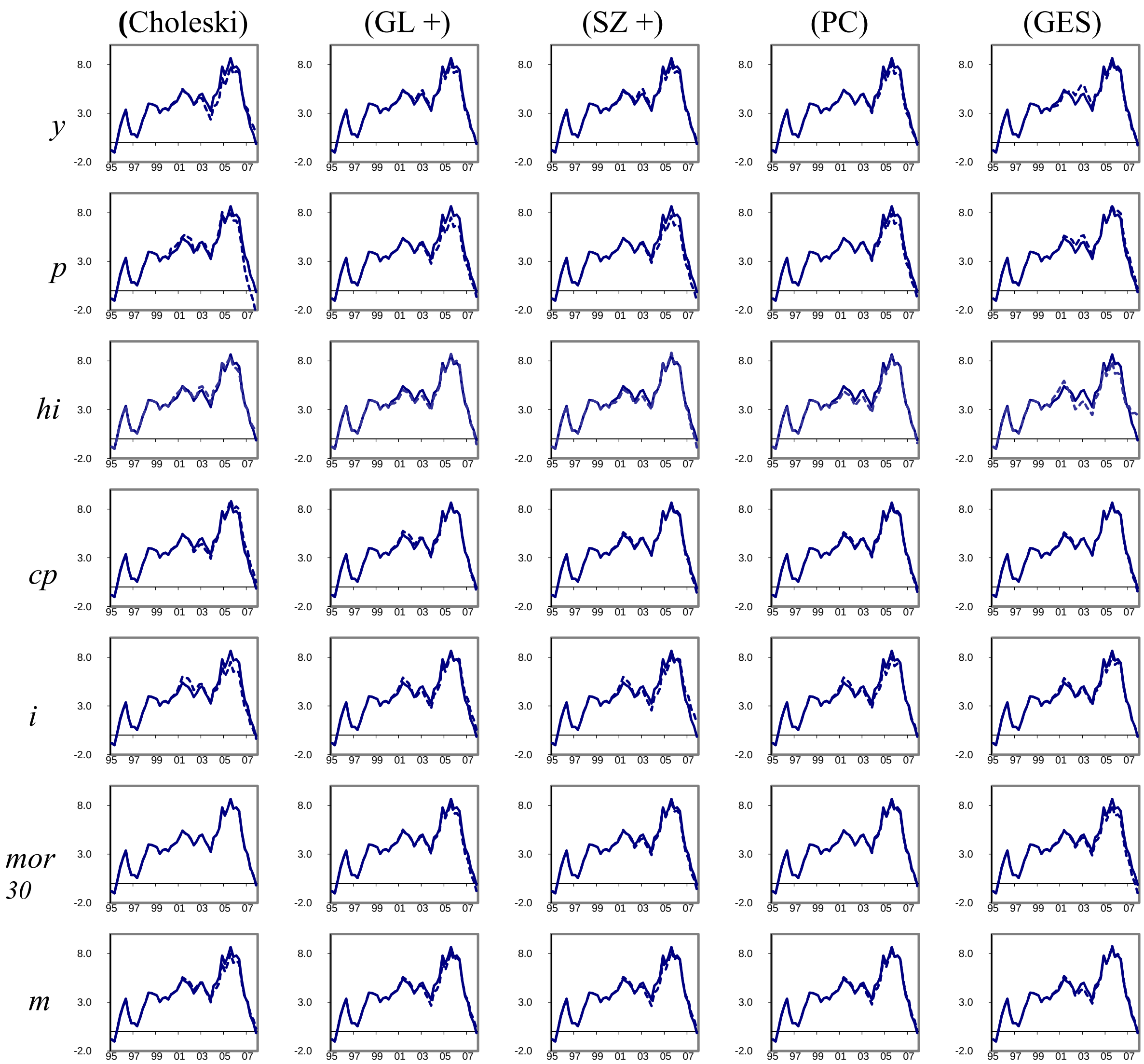

Fig. 3.6. Counterfactual when shutting down each other shock. The solid lines represent actual data and the dotted lines represent the mean value of counterfactual from 1000 realizations when shutting down the structural shock of each variable.

The housing investment (*hi*) case is illustrated in Figure 3.7. For the development since 2000, overall movements are relatively well explained with other variables shocks without its own shocks in the four identifications such as Choleski, GL+, SZ+, and PC except GES. In the GES identification, 2005's high housing investment peak is not explained well without *hi* structural innovations.

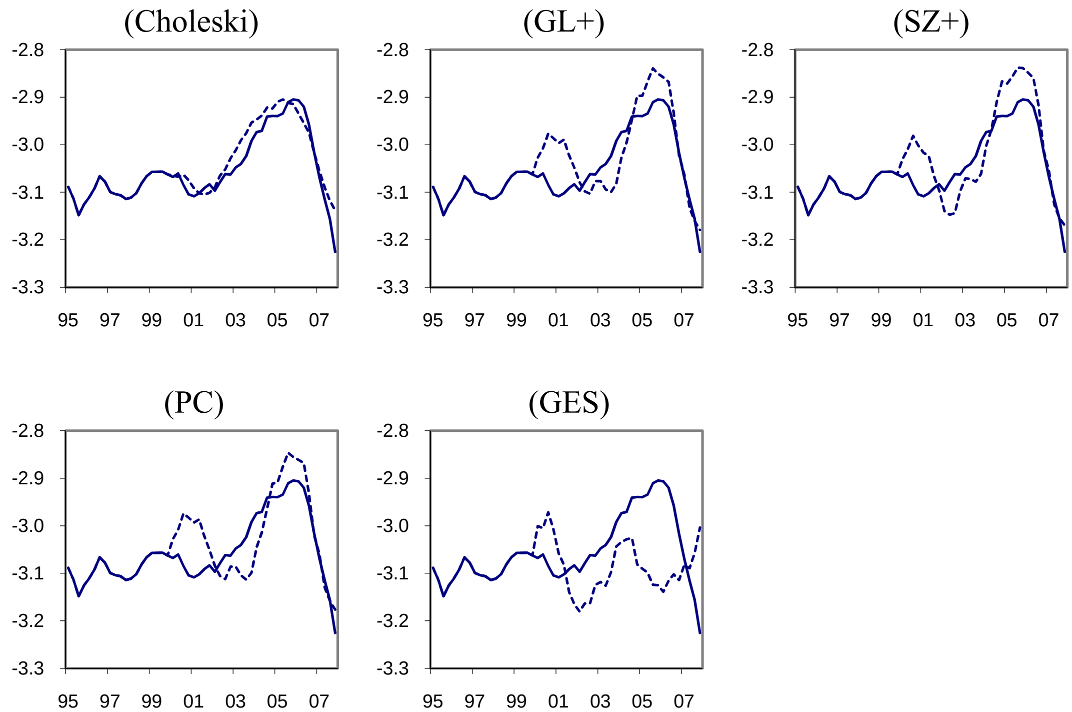

Fig. 3.7. Counterfactual when shutting down housing investment shock. The solid lines represent actual data and the dotted lines represent the mean value of counterfactual from 1000 realizations when shutting down the structural shock of housing investment.

Figure 3.8 displays the counterfactual of housing investment when subsequently shutting down each structural shock. Interestingly, the housing price shock plays a major role in the alternative identifications, except in the GES case where the housing investments shock itself accounts for considerable portion of its developments. One thing that is difficult to explain is the role of mortgage rate. In all identification cases, their roles are much more limited than expected in association with the housing sector.

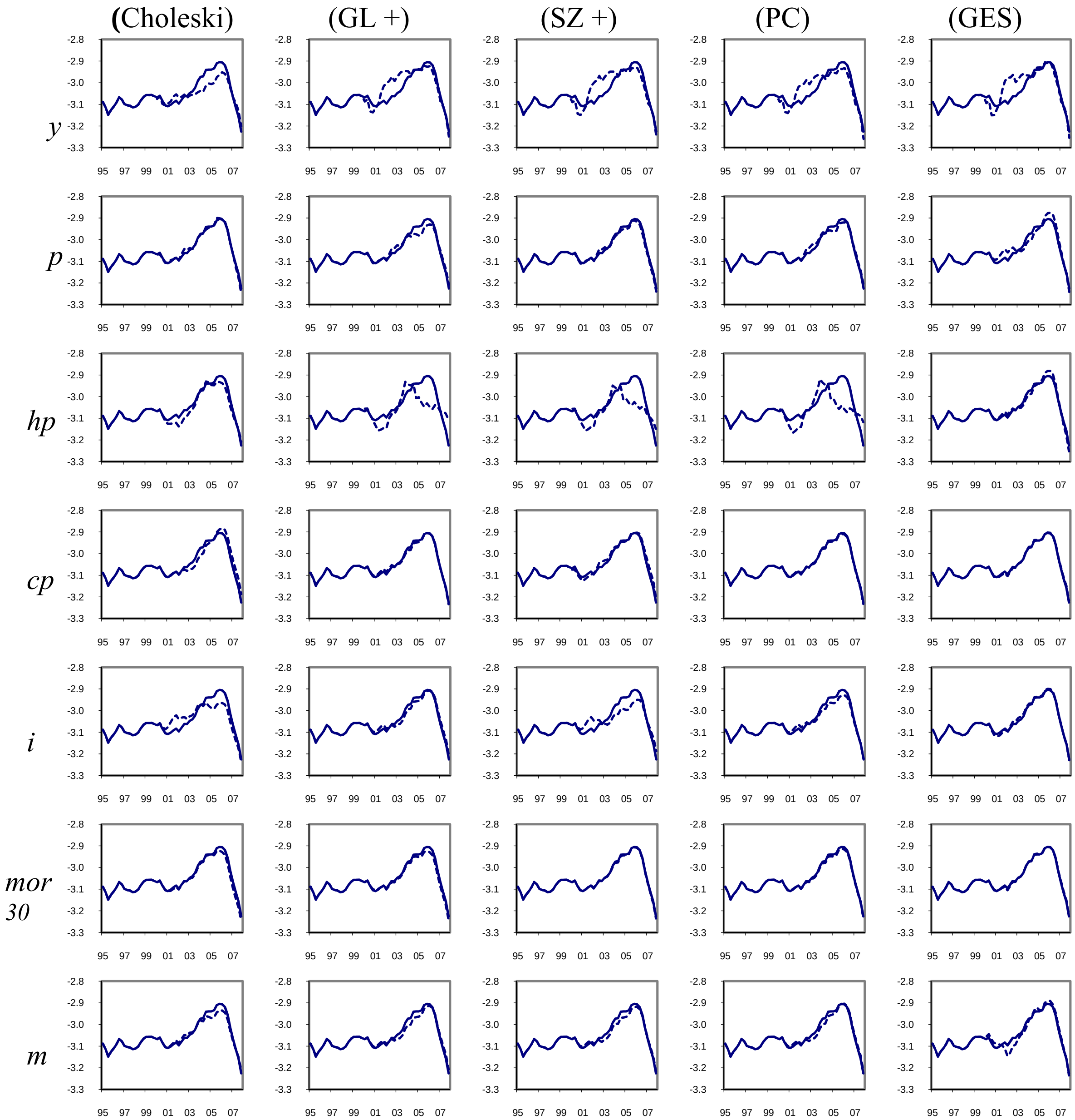

Fig. 3.8. Counterfactual when shutting down each other shock. The solid lines represent actual data and the dotted lines represent the mean value of counterfactual from 1000 realizations when shutting down the structural shock of each variable.

3.5 Conditional Forecast

Finally, conditional forecasts are executed following Wagonner and Zha (1999)'s Gibbs sampling technique which can compute posterior distributions of forecasts in

VARs conditional on paths (or scenarios) of endogenous variables. This simulation method can indicate whether the housing sector can be accounted for or forecasted well if we know the actual paths of macro variables such as real GDP (*y*), inflation (*p*), 30-yr. mortgage rate (*mor30*), money demand (*m*) and FFRs (*i*). Before executing the simulation, the methodology of conditional forecast is summarized. The key point is restricting the structural shocks conditional on the assumed paths such that the structural shocks are the exact difference between forecasts and assumed paths. The simplified bivariate VAR(1) illustration is attached in Appendix D. Following the notation of Jarocinski (2008)[14], the standard VAR equation can be written as equation (23).

$$y_t = B^{-1}B_1 y_{t-1} + B^{-1}B_2 y_{t-2} + \cdots + B^{-1}B_k y_{t-k} + B^{-1}e_t\,,\ e_t \sim iidN(o, I_p) \tag{23}$$

The equation (23) can be rewritten in simplified form as equation (24).

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_k y_{t-k} + Ce_t\,,\ \text{where}\ B^{-1}B_k = A_k\,,\ C = B^{-1} \tag{24}$$

After applying standard companion form, i.e. VAR(1) form, we have equation (25).

$$\tilde{y}_t = F\tilde{y}_{t-1} + G\tilde{e}_t \tag{25}$$

where

$$\tilde{y}_t = \begin{pmatrix} y_t \\ y_{t-1} \\ \vdots \\ y_{t-H+1} \end{pmatrix}_{pH\times 1},\quad F = \begin{pmatrix} A_1 \cdots & A_P \\ I & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & I \end{pmatrix}_{pH\times pH},\quad G = \begin{pmatrix} C & \cdots & 0 \\ 0 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 0 \end{pmatrix}_{pH\times pH},\quad \tilde{e}_t = \begin{pmatrix} e_t \\ 0 \\ \vdots \\ 0 \end{pmatrix}_{pH\times 1}$$

Take $\tilde{y}_{S+h}$ (*h*-ahead forecast), recursively substitute $\tilde{y}_{S+h-1}$, …, $\tilde{y}_{S+1}$ using equation (25). In this way we can obtain y_{S+h} expressed in terms of data up to *S* and subsequent errors.

[14] Actually, he shows only the Choleski identification case, but here it is derived for the generalized identification schemes.

$$y_{S+h} = Ce_{S+h} + \psi_1 Ce_{S+h-1} + \ldots + \psi_{h-1} Ce_{S+1} + F^h_{(1\ldots p,\cdot)} \widetilde{y}_S \tag{26}$$

where ψ_j is the upper left $p \times p$ block of F^j (and $\psi_j C$ is the matrix of orthogonalized impulse responses after j periods) and $F^h_{(1\ldots p,\cdot)}$ is the matrix composed of first p rows of F^h. (This is standard and follows Hamilton (1994, pp 258-260)) The stacked vector of $y_{S+1},\ldots,y_T$ can be written as follows:

$$\begin{pmatrix} y_{S+1} \\ \vdots \\ y_T \end{pmatrix}_{p(T-S)\times 1} = \begin{pmatrix} F^1 \\ \vdots \\ F^{T-S} \end{pmatrix} \widetilde{y}_S + \begin{pmatrix} C & 0 & \cdots & 0 \\ \psi_1 C & C & 0 \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ \psi_{T-S-1} C & \psi_{T-S-2} C & \cdots & C \end{pmatrix} \begin{pmatrix} e_{S+1} \\ e_{S+2} \\ \vdots \\ e_T \end{pmatrix}$$

or shortly as

$$y = H\widetilde{y}_S + R\,e \tag{27}$$

Note that $H\widetilde{y}_S$ is unconditional forecasts from one to T step-ahead. The total length of y is $p(T-S)$ of which q elements are assumed to be known (or given by scenario) and the remaining are unknown. The fact that q elements are known implies q restriction on e, that is, $\widetilde{R}\,e = r$ with $\widetilde{R} = R_{(q,\cdot)}$, $r = y_{(q,\cdot)} - H_{(q,\cdot)}\widetilde{y}_S$ where we also use q as the number of rows of the known ones among y. Note that we keep set conditional structural shocks ($\widetilde{R}\,e$) such that $\widetilde{R}\,e = r$ where $r = y_{(q,\cdot)} - H_{(q,\cdot)}\widetilde{y}_S$, i.e. $\widetilde{R}\,e$ will be the exact difference between scenario (actual realization if the scenario is actual data) and unconditional forecasts. The joint distribution of e and $\widetilde{R}\,e$ is normal as shown in equation (28).

$$\begin{pmatrix} e \\ \widetilde{R}\, e \end{pmatrix} \sim N\left(0,\ \begin{pmatrix} I & \widetilde{R}' \\ \widetilde{R} & \widetilde{R}\widetilde{R}' \end{pmatrix}\right) \tag{28}$$

After applying theorem with respect to conditional normal distribution (Greene (2003), p871-872), we reach final conditional distribution of structural shock as shown in equation (29).

$$e\big|_{\widetilde{R}\, e=r} \sim N\left(\widetilde{R}'(\widetilde{R}\widetilde{R}')^{-1} r,\ I - \widetilde{R}'(\widetilde{R}\widetilde{R}')^{-1}\widetilde{R}\right) \tag{29}$$

The 32 step-ahead forecasts (i.e. forecasts of 2000 Q1 to 2007Q4) of *hp*, *hi* and *cp* conditional on actual realizations of *y, p, m, mor30* and *i* for each identification scheme are generated and compared. For *i*, the simulated FFRs based on the Taylor rule are fed as well as actual *i*. Following Taylor (1993), the simulated FFRs by the Taylor Rule are calculated with equation (30). 3.0% is used as the equilibrium real GDP growth rate, i.e. $\bar{y} = 3.0\%$. Equation (30) indicates that if both inflation and real GDP are at the target, then the federal funds rate would be 4%, which implies a 2% real "equilibrium" rate. Figure 3.9 shows the actual and simulated FFR developments. From 2000 to mid-2001, simulated FFRs are lower than actual ones; since 2002, actual FFRs are lower most of time.

$$i_t = p_t + 0.5(y_t - \bar{y}) + 0.5(p_t - 2) + 2 = 4 + 0.5(y_t - \bar{y}) + 1.5(p_t - 2) \tag{30}$$

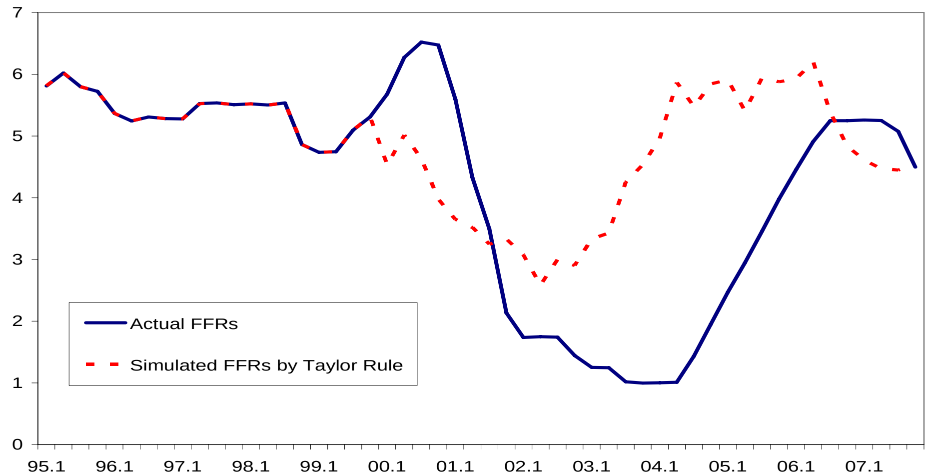

Fig. 3.9. Actual and simulated FFRs. The solid line is actual and dotted line is simulated FFRs respectively.

Conditional forecasts of *hp* are displayed in Figure 3.10 for each identification scheme. The common and conspicuous feature is that given the assumption that we had known the actual paths of *y*, *p*, *m*, *mor30*, and *i* since 2000, the conditional forecast of housing price is much different from the actual realizations in all four alternative identifications. Even when we assume that Fed had followed the ideal path recommended by the Taylor rule, the conditional forecast results change little. For the Choleski case, the conditional forecasts' differences between actual and simulated FFRs are relatively larger than in any alternative identifications'. Even in the Choleski case, however, the conditional forecasts of *hp* cannot emulate fully the sharp increase then sudden drop of housing prices since 2003.

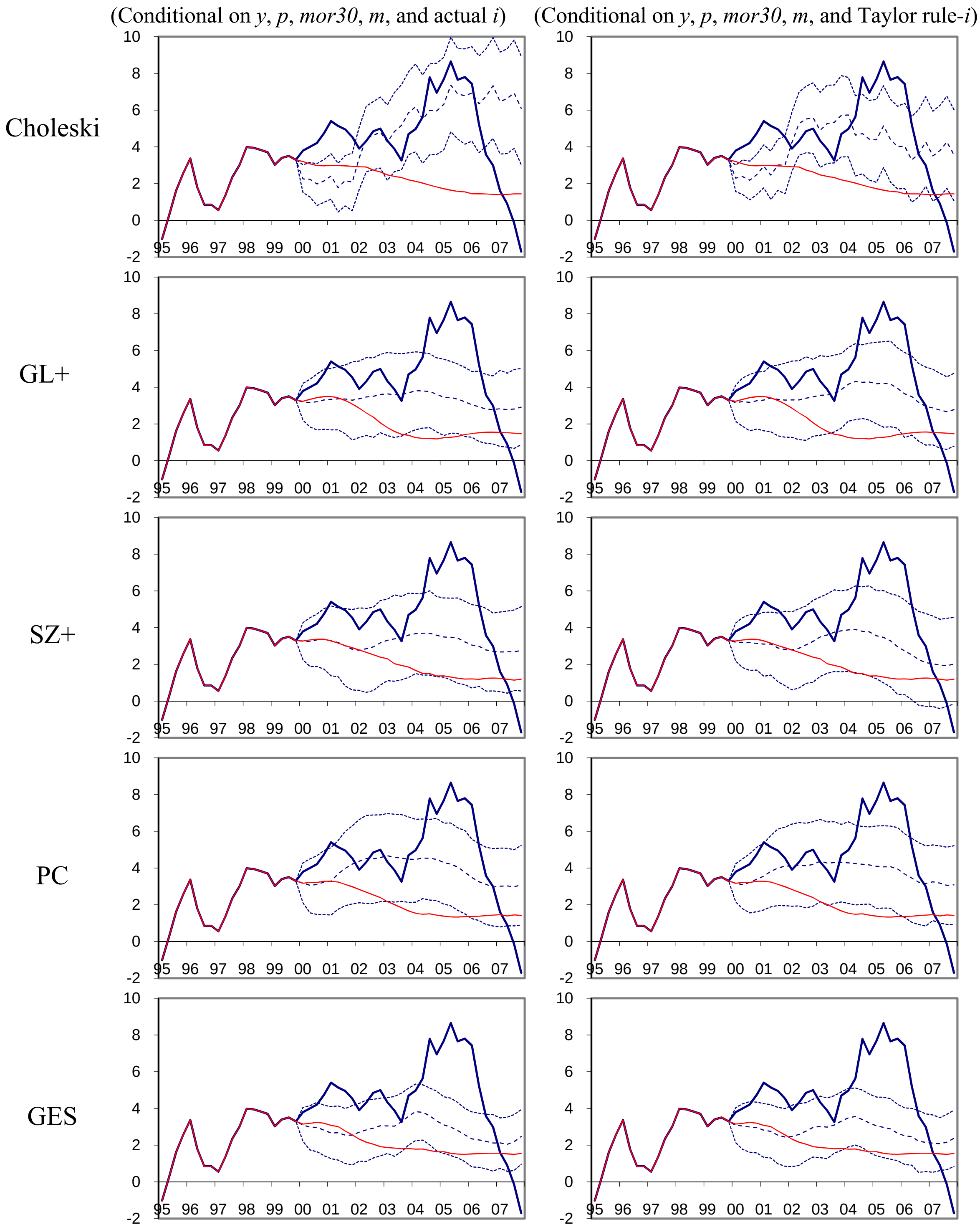

Fig. 3.10. Conditional forecast of housing price. Bold solid lines represent actual data, light solid lines represent unconditional forecast, and dotted lines represent conditional forecast and 68% probability bands.

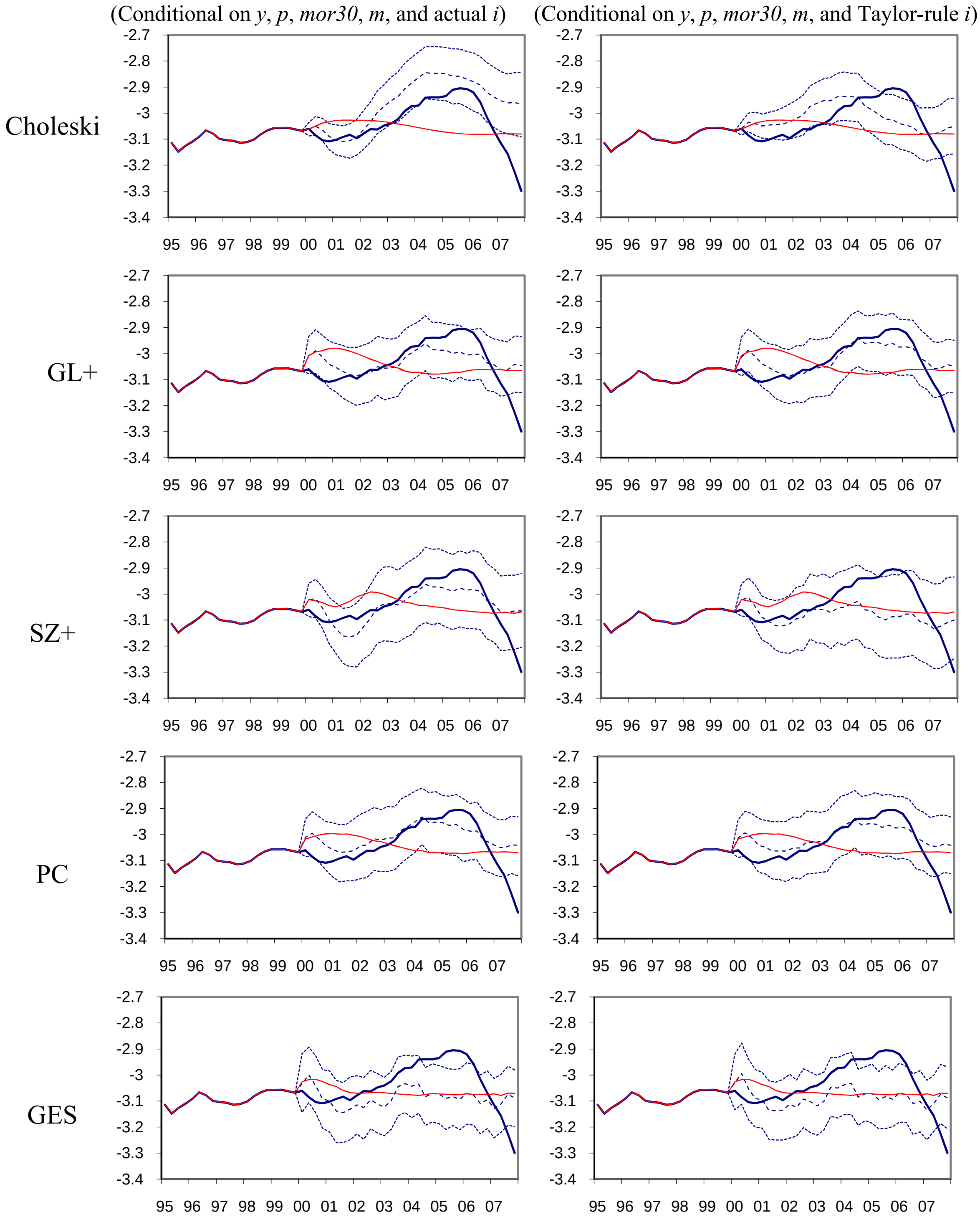

Fig. 3.11. Conditional forecast of housing investment. Bold solid lines represent actual data, light solid lines represent unconditional forecast, and dotted lines represent conditional forecast and 68% probability bands.

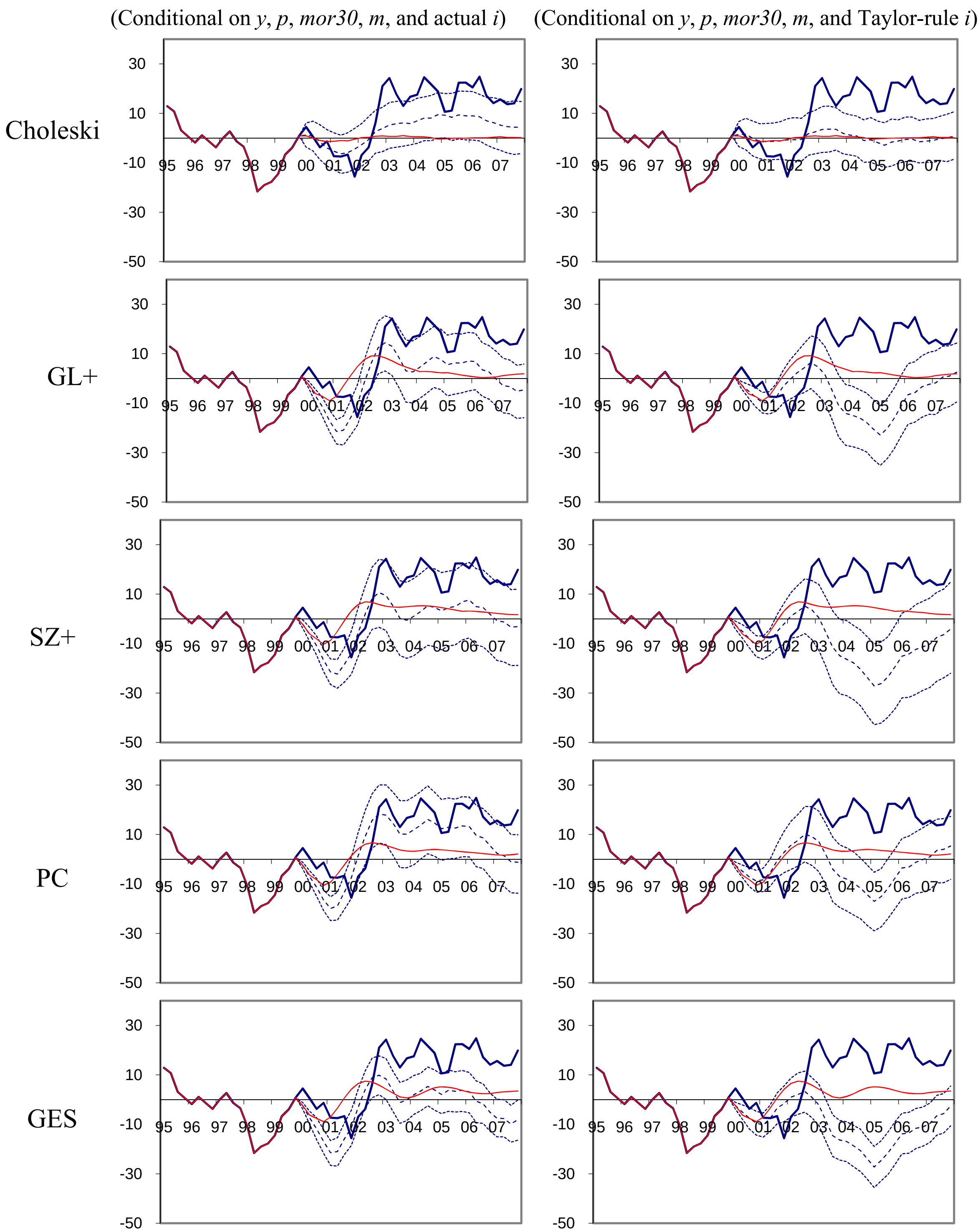

Fig. 3.12. Conditional forecast of commodity price. Bold solid lines represent actual data, light solid lines represent unconditional forecast, and dotted lines represent conditional forecast and 68% probability bands.

Figures 3.11 and 3.12 illustrate the cases of *hi* and *cp* respectively. For *hi* (housing investment), the conditional forecasts vary across the identifications. The 68% probability band can cover a considerable portion of actual realizations since 2000 in all identification schemes, while the forecasts have hardly caught any sudden drop since 2006. Interestingly, the *cp* (commodity price, i.e. Dow-Jones spot average)'s conditional forecasts show a somewhat huge drop in all identification schemes except Choleski's when feeding simulated path of FFRs which are higher overall than actual FFRs. This finding is consistent with the magnitude of impulse-response results which indicate that the *cp* drops relatively more for positive FFRs' shocks in all alternative identifications.

3.6 Concluding Remarks

In this chapter, the superior performance of using steady state BVAR methodology in out-of-sample forecasts, especially for the long horizon, is demonstrated. This result is based on exploiting all information available through both dynamic and deterministic components, which leads to escaping the usual "curse of dimension problem" in VAR framework. Identification issues are explored through two different approaches. One approach is based on associated economic theory; the other is based on algorithms of inductive causation called "DAGs". Both approaches, however, show somewhat similar specifications for the housing sector, while other economic variables' exogenous status is quite different across the two approaches.

The main question is how the monetary policy shock can affect the housing sector. The impulse response of housing price and investment to FFRs in all alternative identifications illustrate that the magnitudes are relatively smaller, less significant, and shorter when compared to the Choleski case. Also, this finding can be confirmed by historical decomposition analysis which confirms that the recent high peak in housing price cannot be well accounted for except by the housing price shock itself. Finally, generated conditional forecasts of housing price also fail in replicating the run-up of housing price around 2005 given the assumption that we had known the actual paths of real GDP (*y*), inflation (*p*), money demand (*m*), 30-yr. mortgage rate (*mor30*) and actual or simulated FFRs based on the Taylor rule. Upon all these estimation results, it is hard to agree with the argument that the considerable responsibility of the current housing boom and fallout is due to monetary policy shocks, even though some portion can be attributed as such. Rather, it can be said that there is still enormous uncertainty and gap in knowledge regarding the relationship between the monetary policy and housing price. Institutional shocks such as fundamental change of mortgage markets including the mobilizing the mortgage debts could probably compose the “unknown uncertainty”.[15] In addition, the recent boom of housing price seems to be a “bubble” in the sense that its movements around 2005 could not be well accounted for by economic fundamentals. It is worthwhile to mention that for inducing soft-landing of the housing price, solely depending on interest rate instrument does not seem to be an efficient measure as Fisher (2008) points out.[16]

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[15] For detailed and further explanation about institutional effect, see DiMartino and Duca (2007).

[16] Fisher (2007) writes “Even as I have been cutting the FFR…interest rates for private sector borrowers have not fallen correspondingly, and rates for some borrowes have increased….To address this problem, I have created some new facilities to bridge over the currently dysfunctional system…”.

Further research about the identification involving housing sectors, which could generate a huge effect on the entire real economy as we have seen, is needed. The relationship between the housing sector and macroeconomic variables, including monetary policy on the environments of considering the institutional factors, is still a looming question.

CHAPTER IV

NONLINEARITY AND STRUCTURAL BREAK IN FORWARD-LOOKING INTEREST RATE RULE

4.1. Introduction

On September 18, 2007, the financial market was shocked by the Fed's official announcement that it would cut Federal fund's target rate by 0.50%p in response to the financial market turmoil triggered by the collapse of the sub-prime housing market. Unlike the expectations of the market, i.e. an at most 0.25%p cut, Bernanke, chairman of the Federal Reserve System, went for swift and bold response to the stock price down turn, reflecting growing fears of the financial market in light of his concern about inflation movements, Fed's first concern.

There are numerous papers that examine the relationships between asset prices and monetary policy. Most of them, however, usually confirm to two conventional ideas: (1) the Fed raises short-term real interest rates in response to inflation (2) meanwhile, the Fed does not change policy in response to stock price movements as Dupor and Conley (2004) point out. In this chapter, we restrict our interest to what the Fed has done in dealing with asset price movements rather than what the Fed *should* do about it. For the former question, basically Dupor and Conley's (2004) argument is revisited based on a newly constructed nonlinear framework. The latter question can be rephrased to ask whether or not the Fed should have a preemptive response to asset price movements. Bernanke and Gertler (1999, 2001) support a quite cautious approach opposing preemptive action, while Bordo and Jeanne (2002) assert that it is better-off to have a preemptive response.

Dupor and Conley (2004) argue that Fed might be more successful in raising (or lowering) the interest rate in resposne to non-fundamental stock price movements during a low inflation era. That is, since the early 1990s, the so-called low inflation era, Fed has more easily or boldly responded to non-fundamental stock price movements given its first concern, i.e. low and stable inflation, is achieved. They show this using a forward-looking interest rate rule based on GMM developed by Clarida, Gali, and Gertler (2000).

After replicating their estimation results with extended data set, it is found that their linear estimation results are not robust to the chosen breakpoint. They say that the first quarter of 1991 is chosen because, since then, inflation has never grown at a rate greater than 4%. Even though they do not provide any econometric analysis to back up their choice, this breakpoint seems plausible. Along the low inflation period beginning in the early 1990s, the so-called 'Great Moderation' era comes and discussion of 'New Economy' follows. The experiments show how the estimation results change to small variations around breakpoints. The estimation consequences are unexpected and unacceptable, revealing huge deviations.

How can this problem be fixed? This question is the starting motivation of this chapter. An alternative way of relaxing this problem is introducing a nonlinear model. A nonlinear model of forward-looking interest rate rule based on 'series method' is constructed, which allows us to carry over the original GMM presentation. After establishing nonlinear model, we revisit Dupor and Conley's (2004) argument which examines structural break in Fed's behavior with the interesting hyppthesis that between nonlinearity and structural change which is the dominant cause of the apparent changes in Fed behavior.

Upon extended instrumental variables (IVs) set-up based on Andrews (1999), estimated test results show that both nonlinearity and structural change matter in explaining the Fed's behaviors responding to inflation and stock price gap movements. When looking at time-varying coefficients movements, somewhat different impressions come out across inflation and stock price gap coefficients. Given structural change, inflation coefficient's movements indicate that Fed has responded to expected inflation pressure nonlinearly across sub-periods, while stock price gap coefficient's show explicit break around the early 1990s, confirming Dupor and Conley's finding.

The remainder of this chapter is organized as follows. In section 4.2, the forward-looking interest rate rule, including stock price gap variable, is derived and specified; this is the main theoretic background associated with this analysis. In section 4.3, data series are described and linear estimation results which are similar to those of Dupor and Conley (2004) are discussed. Then, with this linear model, the non-robustness around chosen breakpoint is dealt with. In section 4.4, the nonlinear model based on series method is constructed and its estimation results and time-varying coefficients movements discussed. In section 5, the test of structural change with the nonlinear framework is explored. Finally, the concluding remarks are drawn in section 4.5.

4.2. Fed's Policy Reaction Function: A Forward-looking Rule

John Taylor examines Fed's policy reaction function, i.e. interest rate policy, using contemporaneous or previous variables. He uses previous four-quarter inflation rate (Taylor 1993) or current inflation rate (Taylor 1998). Clarida, Gali, and Gertler (2000) newly build up the forward-looking policy rule and apply it to exploring post-war U.S. monetary policy reaction behavior. In this methodology, the GMM tool plays a central role in relaxing the endogenous problem which is in the conventional Taylor rule using OLS. In addition, their methodologies differ in two ways. Literally, it is forward-looking, i.e. not using contemporaneous or previous variables. Also, it introduces the speed of adjustment (ρ) reflecting Fed's realistic behavior of 'fine tuning'. Dupor and Conley (2004) add stock price gap variable to the forward-looking policy rule and discuss their estimation results. Thus, the forward-looking interest rate rule is first derived following Clarida et al. (2000). Simple forward looking rule can be written as equation (31).

$$R_t^* = R^* + \alpha[E(\pi_{t+k} \mid \Omega_t) - \pi^*] + \beta E(y_{t+k} \mid \Omega_t) + \gamma s_t \tag{31}$$

where R_t^* is target rate for nominal interest rate (e.g. Federal Funds Rate), R^* is desired nominal rate when both inflation and output are at their target levels, π_{t+k} is k-quarter ahead growth rate of GDP deflator (annual rates), Ω_t is information set up to t when interest rate is set, π^* is target for inflation, and y_{t+k} is k-quarter ahead percentage deviation of real GDP from its' Hodrick-Prescott trend, which represents output gap beyond natural rate of growth. Finally, s_t is stock variable gap at time t. It should be mentioned that the reason for using current stock variable gap, unlike in inflation and output gap, is based on Fed's plausible behavior such that Fed is more likely to respond to stock price after watching current movement rather than based on expected stock price movements, as Dupor and Conley (2004) point out.

Two identities represent short ($r_t^* \equiv R_t^* - E(\pi_{t+k} \mid \Omega_t)$) and long-run Fisher equation ($r^* \equiv R^* - \pi^*$) respectively associated with the relationship between real and nominal interest rates where r^* is long-run equilibrium real rate, which is assumed constant and independent of monetary policy. After substituting the above two equations into (31), ex ante implied real rate rule can be written as equation (32).

$$r_t^* = r^* + (\alpha - 1)[E(\pi_{t+k} \mid \Omega_t) - \pi^*] + \beta E(y_{t+k} \mid \Omega_t) + \gamma s_t \tag{32}$$

The basic intuition that equation (32) indicates is simple and clear; that is, interest rate rules characterized by $\alpha > 1$ imply active or aggressive responses to expected rising inflation, while those with $\alpha < 1$ are likely to be accommodative of inflation shocks. A similar logic can be applied to output gap coefficient β and stock price gap γ, i.e., active or aggressive response to output gap if $\beta > 0$ and stock variable gap if $\gamma > 0$ while accommodative otherwise. Since the policy rule represented by equation (31) totally ignores Fed's tendency to smooth changes in interest rates, we need to consider more realistic adjustment of interest rate to the target rate R_t^* as follows:

$$R_t = \rho R_{t-1} + (1 - \rho) R_t^* \tag{33}$$

where R_t is "actual" interest rate (i.e., actual Federal Funds Rate). Equation (33) implies that, in each period, Fed adjusts her interest rate with a fraction $(1 - \rho)$ of its' current target level. The gap between current interest rate and current target level can be represented by some linear combination between one-period previous realized actual interest rate and its current target level. Finally, after substituting equation (31) into (33) and using long-run Fisher equation ($r^* \equiv R^* - \pi^*$), we can obtain testable forward-looking interest rate rule as follows:[17]

$$R_t = \rho R_{t-1} + (1-\rho)[\theta + \alpha\pi_{t+k} + \beta y_{t+k} + \gamma s_t] + e_t \tag{34}$$

where $\theta = r^* - (\alpha - 1)\pi^*$ and $e_t = (1-\rho)[\alpha(E\pi_{t+k} \mid \Omega_t - \pi_{t+k}) + \beta(Ey_{t+k} \mid \Omega_t - y_{t+k})]$, that is, e_t is linear combination of forecasting error and, thus, orthogonal to any variables in the information set Ω_t. Let Z_t denote a vector of instruments known when R_t is set (i.e., $Z_t \in \Omega_t$); then, we can have orthogonal condition to estimate parameters (*ρ, θ, α, β, and γ*) using GMM (Hansen, 1982) as equation (35).

$$E(e_t Z_t) = E\{[R_t - \rho R_{t-1} - (1-\rho)(\theta + \alpha\pi_{t+k} + \beta y_{t+k} + \gamma s_t)]\, Z_t\} = 0 \tag{35}$$

4.3 Linear Model and Break-point Issue

All data employed in this analysis are on a quarterly average basis. From Table 4.1, we can see specific descriptions for each series. Basically, every data set is the same

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[17] The concrete deriving steps can be described as follows. After substituting equation (31) into (33), we obtain below equation. $R_t = \rho R_{t-1} + (1-\rho)[R^* + \alpha(E_t\pi_{t+k} \mid \Omega_t - \pi^*) + \beta E_t y_{t+k} \mid \Omega_t + \gamma s_t]$

Now substituting long-run Fisher equation $r^* \equiv R^* - \pi^*$, and rearranging yields equation (37).

$$\begin{aligned}
R_t &= \rho R_{t-1} + (1-\rho)[r^* + \pi^* + \alpha(E_t\pi_{t+k} \mid \Omega_t - \pi^*) + \beta E y_{t+k} \mid \Omega_t + \gamma s_t] \\
&= \rho R_{t-1} + (1-\rho)[r^* - (\alpha-1)\pi^* + \alpha E\pi_{t+k} \mid \Omega_t + \beta E y_{t+k} \mid \Omega_t + \gamma s_t] \\
&= \rho R_{t-1} + (1-\rho)[r^* - (\alpha-1)\pi^* + \alpha\pi_{t+k} + \beta y_{t+k} + \gamma s_t] \\
&\qquad + (1-\rho)[\alpha E\pi_{t+k} \mid \Omega_t + \beta E y_{t+k} \mid \Omega_t - \alpha\pi_{t+k} - \beta y_{t+k}] \\
&= \rho R_{t-1} + (1-\rho)[r^* - (\alpha-1)\pi^* + \alpha\pi_{t+k} + \beta y_{t+k} + \gamma s_t] \\
&\qquad + (1-\rho)[\alpha(E\pi_{t+k} \mid \Omega_t - \pi_{t+k}) + \beta(E y_{t+k} \mid \Omega_t - y_{t+k})] \\
&= \rho R_{t-1} + (1-\rho)[\theta + \alpha\pi_{t+k} + \beta y_{t+k} + \gamma s_t] + e_t
\end{aligned}$$

as those used in Dupor and Conley (2004). 21 IVs from lag variables are chosen. Slight difference come in the IVs associated with the stock price gap variable. One through five lags of IVs are used instead of one and five lags like Dupor and Conley (2004) use, since just choosing one and five lags is awkward when adopting the lags as IVs even though they justify it as the first lag representing short-run information and fifth lag long-run information of stock price gap movements.

Table 4.1
Data description

variables	Quarterly Average Basis[1)]
R_t	Federal Funds rates
π_t	Annualized growth rate of GDP deflator
y_t	Percentage deviation of real GDP from its Hodrick-Prescott (HP) trend y_t
s_t	Two year growth rate of the S&P 500 price earning ratio (PER)
Instrumental Variables (21)	Constant Three lags of π_t and y_t Three lags of quarterly growth rate in producer price index and M2 Three lags of the yield spread between long- and short-term government bond[2)] Five lags of two year growth rate of the S&P 500 price earning ratio (PER)[3)]

Notes: 1) All data except S&P 500 price earning ratio (PER) are obtained from Ib-based database (FRED) in Federal Reserve Bank of St. Louis. 2) I use yield spread between 10 year and 3 month U.S. Treasury bonds. 3) The data are obtained from Dr. Robert J. Shiller's homepage.

Especially for stock price gap variable, price-earning ratio is used. The earning part represents fundamental factors which eventually decide stock price trends. Thus, high price-earning ratio can be regarded as positive stock price gap. Using two years growth rate of stock price gap can be explained by economic intuition. Dupor and Conley (2004) point out, "We use a two-year price-earnings growth rate instead of short-term one. It seems more plausible that the Federal Reserve would respond to lowerfrequency changes in a stock price index or a price-earning ratio than to higher-frequency changes."

In late 1979, Paul Volcker started his appointment as a Fed chairman. After experiencing huge turmoil and fallout of real economy affected by the high inflation, he sent a strong and explicit signal to the market that Fed would curb the inflation as a first priority. This fundamental shift in monetary policy leads us to adopt 1979 as a natural starting point of the analysis as Dupor and Conley (2004) do. Figure 4.1 displays inflation movements of U.S. and the data starting point as well as the chosen breakpoint.

Dupor and Conley (2004) choose 1Q 1991 as a breakpoint because, since then, there has never been greater than 4% growth rate in inflation. Even though they do not provide any econometric analysis to back their choice, this chosen breakpoint looks plausible. Along the low inflation period beginning in the early 1990s, the so-called 'Great Moderation' era comes and the discussion of 'New Economy' follows. However, non-robustness of estimation results of Dupor and Conley's linear model around this breakpoint can be found.

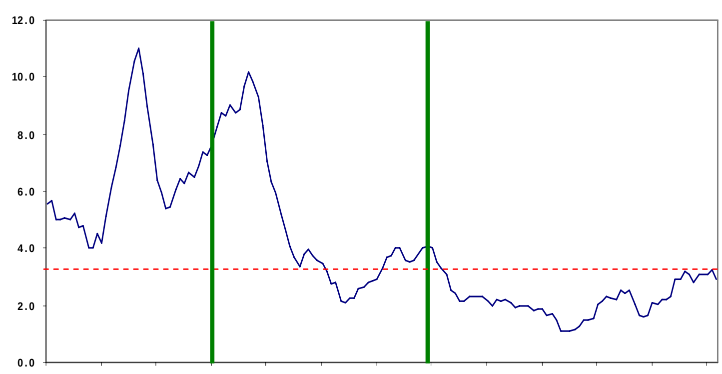

Fig. 4.1. Inflation movements. First line indicates data starting point and second line chosen break point by Dupor and Conley (2004).

Briefly describing the methodology associated with GMM, forward-looking horizon is one year, i.e., *k=4* in quarterly data framework and time series-HAC estimation is conducted using identity weighting matrix. Also, Bartlett kernel with Newey-West's fixed bandwidth selection and VAR1 pre-whitening is involved as an optional choice. So, basically, the magnitudes of coefficients are equivalent to those of 2SLS but the standard errors are different.

$$R_t = \rho R_{t-1} + (1-\rho)[\theta + \alpha\pi_{t+k} + \beta y_{t+k}] + e_t \tag{36}$$

Table 4.2
Interest rate rules in high and low inflation sub-periods[1)]

Period	***α***	***B***	***ρ***	***θ***	***J-statistic***[2)]
1979:4 – 2005:4	3.292 (0.815)	3.245 (1.672)	0.893 (0.044)	-3.783 (2.825)	9.818 [0.911]
1979:4 – 1991:1	1.386 (0.248)	-0.477 (0.247)	0.659 (0.108)	3.646 (1.189)	12.407 [0.775]
1991:2 – 2005:4	18.500 (91.405)	15.418 (65.419)	0.988 (0.052)	-40.064 (215.5)	9.370 [0.927]

Note: 1) Standard errors appear in parentheses. 2) P-values associated with a test of the model's over-identifying restrictions under the null that over-identifying restrictions are satisfied appear in brackets.

The estimation equation and results of the linear model without stock price gap are shown in equation (36) and Table 4.2 respectively. Overall results are similar to those of Dupor and Conley (2004). Full sample and high inflation sub-period estimation results look fine. The speed of adjustment (1-ρ) is faster in the high inflation sub-period which is consistent with Fed's historical behavior. One interesting point is an inflation coefficient greater than one and significant in both the full sample and high inflation sub-period. There is, however, a somewhat large deviation already in the estimation of the inflation coefficient in the low inflation sub-period, and it is insignificant. In addition, other parameters are estimated imprecisely. As Dupor and Conley (2004) point out, the degree of variation matters. Compared to the high inflation sub-period, the variation of inflation movements in low inflation is too low to generate significant coefficients.

When including the stock price gap variable, the estimation equation and results are displayed in equation (37) and Table 4.3 respectively. The overall precision of estimation results is improved and we can easily notice sharp change in stock price gap coefficients across sub-periods confirming Dupor and Conley's argument. That is, the coefficient of stock price gap is positive and significant in the low inflation sub-period while it is statistically close to zero in other sub-periods.

However, we still have insignificance of inflation coefficient in the low inflation sub-period. This is a very inconvenient result. Does it mean that Fed does not care about inflation since the start of the low inflation era? Put other way, can we directly state that Fed has done nothing associated with expected inflation pressure since the early 1990s? Not really. Faced with this type of identification problem, Dupor and Conley (2004) try to explain using the argument that, "If U.S. monetary policy aggressively combats inflation, and then price-setters would never choose time paths with period-on-period price increases. To do so would mean…putting them out of business. In equilibrium, one would never observe high inflation." This argument could be the answer we seek. However, when facing huge deviations in estimation results in the linear model around the breakpoint, other alternative approaches to relax this problem must be sought by constructing a nonlinear model.

$$R_t = \rho R_{t-1} + (1-\rho)[\theta + \alpha\pi_{t+k} + \beta y_{t+k} + \gamma s_t] + e_t \tag{37}$$

Table 4.3
Interest rate rules with stock variable[1)]

Period	***α***	***β***	***ρ***	***θ***	***γ***	***J-statistic***[2)]
1979:4 – 2006:1	2.888 (0.555)	1.509 (1.186)	0.858 (0.052)	-3.123 (1.968)	0.055 (0.025)	8.474 [0.933]
1979:4 – 1991:1	1.355 (0.320)	-0.470 (0.264)	0.653 (0.128)	3.843 (1.633)	-0.004 (0.020)	12.428 [0.714]
1991:2 – 2005:4	2.273 (2.582)	-0.944 (1.201)	0.885 (0.061)	-2.518 (6.253)	0.129 (0.057)	7.073 [0.972]

Note: 1) Standard errors appear in parentheses. 2) P-values associated with a test of the model's over-identifying restrictions under the null that over-identifying restrictions are satisfied appear in brackets.

To evaluate how robust the estimation results of the linear model to the chosen breakpoints are, some experiments are carried out demonstrating how much the estimation results can change when shifting the break point by adding or subtracting one quarter around the chosen breakpoint up to one year. As shown in Tables 4.4 and 4.5, small variations of breakpoints lead to huge deviations in estimation results, especially in inflation coefficients in the low inflation sub-period. For the coefficient of stock price gap, the significance varies a lot across the sub-period. These results are shocking because even shrinking just one quarter of the low inflation sub-period demonstrates the reversal of sign in the estimated inflation coefficient in the case without stock price gap.

Table 4.4
Robustness test of the estimation without stock variable

(Low)	1990.2~	1990.3~	1990.4~	1991.1~	**1991.2~**	1991.3~	1991.4~	1992.1~	1992.2~
Inflation	4.138 (6.059)	2.567 (4.340)	1.443 (3.724)	1.530 (4.758)	**18.500** **(91.405)**	-24.805 (83.581)	-15.635 (28.909)	-9.503 (7.616)	-8.908 (6.650)

Note: Standard errors appear in parentheses.

Table 4.5
Robustness test of the estimation with stock variable

(Low)	1990.2~	1990.3~	1990.4~	1991.1~	**1991.2~**	1991.3~	1991.4~	1992.1~	1992.2~
Inflation	1.122	0.965	0.842	0.792	**2.273**	4.092	7.228	21.908	22.134
	(1.009)	(1.131)	(1.304)	(1.510)	**(2.582)**	(4.815)	(10.139)	(68.029)	(57.741)
Stock	0.104	0.101	0.096	0.096	**0.129**	0.168	0.212	0.458	0.500
	(0.018)	(0.021)	(0.026)	(0.033)	**(0.057)**	(0.105)	(0.198)	(1.191)	(1.124)

Note: Standard errors appear in parentheses.

Despite the plausible breakpoint based on economic episodes, why does this deviation occur? One way of accounting for this could be weakness of stationary assumption of interest rate. However, the stationary assumption of interest rate has been given from the Taylor's analysis and this type of policy reaction function. As an alternative, the construction of a nonlinear model to relax this problem is explored. After constructing nonlinear model, Dupor and Conley (2004)'s argument will be revisited.

4.4 Nonlinear Model

When considering nonlinear model, there are several options. The STAR model of Terasvirta (1994) could be one of them. However, most of them are not consistent with the GMM representation which is core in the forward-looking policy rule. So we adopt the so-called 'series method' which can allow polynomial terms in inflation and stock price gap coefficients generating nonlinearity while it cannot harm the beauty of original GMM specification.

In the series method, the inflation and stock variable coefficients can be approximated by a function of chosen explanatory variables. The potential candidates for them could be level value of inflation, inflation deviation from its target level, level value of interest rate, and some possible combinations. However, they all fail to generate nonlinearity except volatility of FFRs (or deviations from its trend). Hereafter, it will be denoted by δ_t. Equation (38) illustrates nonlinear specification expressed by coefficient functions.

$$E(e_t Z_t) = E\{[R_t - \rho R_{t-1} - (1-\rho)(\theta + \alpha(\delta_t)\pi_{t+k} + \beta y_{t+k} + \gamma(\delta_t)s_t)]\, Z_t\} = 0 \qquad (38)$$

where δ_t = R_t - (HP Trend of R_t). Each coefficient function is approximated by polynomial terms and it can be represented as $\alpha(\delta_t) \approx \alpha_o + \alpha_1\delta_t + \alpha_2\delta_t^2 + \cdots + \alpha_{k_1}\delta_t^{k_1}$ and $\gamma(\delta_t) \approx \gamma_o + \gamma_1\delta_t + \gamma_2\delta_t^2 + \cdots + \gamma_{k_2}\delta_t^{k_2}$. If we express this specification in matrix form, we can have clear intuition that the linear model is just one specific case among a variety of possible nonlinear models. The linear model can be true only when the restriction of the power values of the polynomial terms are jointly zero, e.g., $k_1 = k_2 = 0$. Equation (39) illustrates nonlinear specification.

$$E(e_t Z_t) = E\{[R_t - \rho R_{t-1} - (1-\rho)(\theta + (\delta_t^{k_1})'\alpha\, \pi_{t+k} + \beta y_{t+k} + (\delta_t^{k_2})'\gamma\, s_t]\, Z_t\} = 0 \qquad (39)$$

where $(\delta_t^{k_1})'\alpha = (1\ \delta_t\ \delta_t^2 \cdots \delta_t^{k_1})(\alpha_0\ \alpha_1\ \alpha_2 \cdots \alpha_{k_1})'$, $(\delta_t^{k_2})'\gamma = (1\ \delta_t\ \delta_t^2 \cdots \delta_t^{k_2})(\gamma_0\ \gamma_1\ \gamma_2 \cdots \gamma_{k_2})'$ and if $k_1 = k_2 = 0$, then nonlinear model is reduced back to a linear model. The selection of nonlinear model is three-folds. First, check the significance of nonlinearity by conducting usual joint Wald test for polynomial coefficient terms. Secondly, watching *p*-values of rejecting linearity in each model, select the series term K by two criteria which are usual in the series method (See Li and Racine (2007), p451-453): 'Mallow's C_L' and 'generalized cross-validation'. First the Mallow's C_L is to select K to minimize $\hat{\sigma}^2[1+\frac{2K}{n}]$.

Second the generalized cross-validation is to select K to minimize $\hat{\sigma}^2/(1-\frac{K}{n})^2$ where

$\hat{\sigma}^2=\frac{1}{n}\sum_{i=1}^{n}u_i^2=\frac{SSR}{n}$ and $K = k_1 + k_2$. Among the final two candidates passing the two steps, look at J-statistics to evaluate the degree of satisfaction in over-identifying restrictions. This selection process is displayed in Table 4.6. Eventually, $k_1 = k_2 = 2$, i.e., quadratic function is selected on the grounds that it is much simpler without losing much in explanation power when compared to the $k_1 = 4$, $k_2 = 2$ case.

Table 4.6
Selection of series term K

Series Term	Mallow's C_L	Generalized cross-validation	Joint Wald Test (Null: linearity)	J-statistic p-value
$k_1 = 2$, $k_2 = 2$*	**0.7925**	**0.7961**	**0.0543**	**0.606**
$k_1 = 2$, $k_2 = 3$	0.8144	0.8202	0.0977	0.560
$k_1 = 2$, $k_2 = 4$	0.8386	0.8472	0.1652	0.487
$k_1 = 3$, $k_2 = 2$	0.8146	0.8204	0.0925	0.508
$k_1 = 3$, $k_2 = 3$	0.8398	0.8484	0.1268	0.452
$k_1 = 3$, $k_2 = 4$	0.7904	0.8015	0.0898	0.447
$k_1 = 4$, $k_2 = 2$*	**0.7499**	**0.7576**	**0.0445**	**0.343**
$k_1 = 4$, $k_2 = 3$	0.7847	0.7956	0.0639	0.279
$k_1 = 4$, $k_2 = 4$	1.0068	1.0251	0.3868	0.163

Note: * implies final candidates. And also note that the quadratic function of inflation coefficient in $k_1 = 2$, $k_2 = 2$ case is not much different from forth-power function in $k_1 = 4$, $k_2 = 2$ case in the quality sense, if not triple one.

Finally, selected nonlinear specification is represented in equation (40). Full sample estimation results of the nonlinear model are shown in Table 4.7. Most of the coefficients are estimated precisely except output gap coefficient (β) and constant (θ).

For this nonlinear model, the nonlinearity test is conducted, and it is found that most nonlinearity power comes from inflation coefficients. Jointly with inflation coefficients, stock price gap coefficients can reject the linearity; meanwhile, they cannot generate nonlinearity on their own.

$$E(e_t Z_t) = E\{[R_t - \rho R_{t-1} - (1-\rho)(\theta + (\alpha_0 + \alpha_1\delta_t + \alpha_2\delta_t^2)\pi_{t+k} + \beta y_{t+k} + (\gamma_0 + \gamma_1\delta_t + \gamma_2\delta_t^2)s_t]\, Z_t\} = 0 \quad (40)$$

Table 4.7
Nonlinear model estimation result: Full sample period

	α_0	α_1	α_2	β	ρ	θ	γ_0	γ_1	γ_2	***J-statistic***
1979:4 – 2005:4	2.486 (0.464)	0.438 (0.159)	-0.058 (0.039)	0.890 (0.883)	0.752 (0.077)	-0.627 (1.339)	0.022 (0.041)	-0.069 (0.038)	-0.026 (0.027)	10.110 [0.606]

Note that the joint Wald coefficient tests are as follows:

Null: $\alpha_1 = \alpha_2 = \gamma_1 = \gamma_2 = 0$: p-value = 0.0543
Null: $\alpha_1 = \alpha_2 = 0$: p-value = 0.0159
Null: $\gamma_1 = \gamma_2 = 0$: p-value = 0.1508

The beauty of the nonlinear model is that we can draw time-varying coefficient movements. It can be obtained from mapping values of estimated quadratic function corresponding to time-varying historical volatility of interest rate (δ_t). Figure 4.2 shows the time-varying movement of the inflation coefficient. This graph shows quite plausible illustration associated with Fed's behavior responding to expected inflation pressure. That is, most of the magnitudes of coefficients fall in reasonable range from one to three, implying that there has been aggressive Fed response to expected inflation pressure across sub-periods. This implication is somewhat different from that of the linear model in which we face difficulty in explaining Fed's reaction to inflation pressure in the low inflation era. Subsequently, a few interesting questions are raised. Is there real structural break? Or isn't nonlinearity dominant over structural change? Which one is the better approach to explain changes in Fed's behavior in this type of reaction analysis?

For the stock price gap coefficient, a similar impression can be raised from the time-varying movements shown in Figure 4.3. It fluctuates around zero across sub-periods, which leads one to think that Fed might be responding nonlinearly to non-fundamental stock price movements, irrespective of structural change. Until thus far, all test results and coefficient movements indicated that the nonlinearity of the coefficients should be considered seriously.

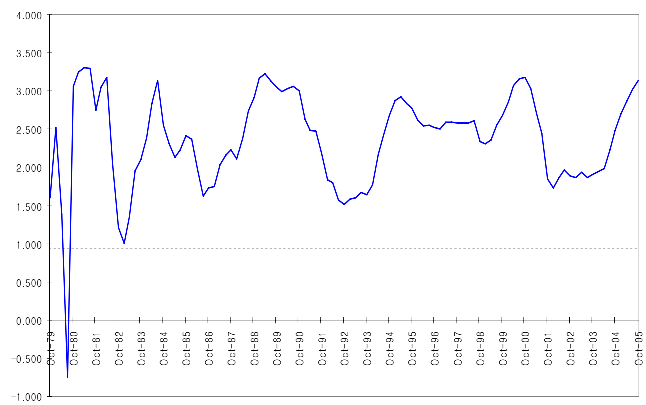

Fig. 4.2. Time-varying inflation coefficient movement.

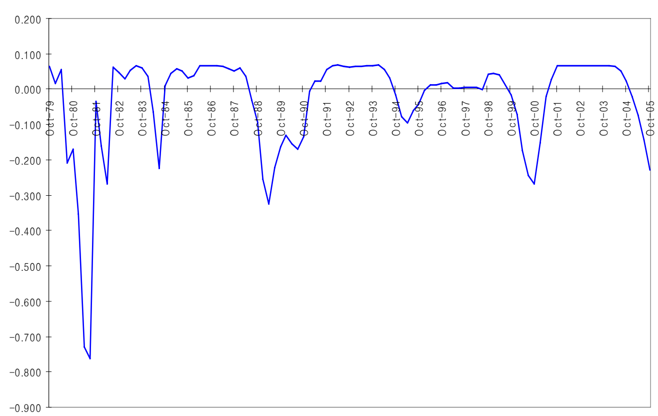

Fig. 4.3. Time-varying stock price gap coefficient movement.

The same experiment is conducted for each sub-period separately. The estimation results show consistency with those of the full sample period in terms of existence and source of nonlinearity. Superscript *h* implies the high inflation sub-period and estimation results are shown in Table 4.8, while *l* implies the low inflation sub-period and estimation results are shown in Table 4.9. Again, each sub-period test's results recommend that the nonlinearity in the policy rule reaction function must be considered when executing the test of structural change across sub-periods.

Sub-sample h : t ≤ t*, t*= 1991 q1

$$E(e_t^h Z_t) = E\{[R_t - \rho^h R_{t-1} - (1-\rho^h)(\theta^h + (\alpha_0^h + \alpha_1^h \delta_t + \alpha_2^h \delta_t^2)\pi_{t+k} + \beta^h y_{t+k} + (\gamma_0^h + \gamma_1^h \delta_t + \gamma_2^h \delta_t^2)s_t] Z_t\} = 0 \quad (41)$$

Table 4.8
Nonlinear model estimation result: High inflation sub-period

	α_0	α_1	α_2	β	P	θ	γ_0	γ_1	γ_2	*J-statistic*
1979:4 – 1991:1	2.244 (0.853)	0.297 (0.107)	-0.014 (0.025)	0.834 (0.865)	0.712 (0.118)	0.792 (3.334)	-0.057 (0.043)	-0.014 (0.023)	0.025 (0.025)	8.622 [0.735]

Note that the nonlinearity tests are as follows:

$$Null: \alpha_1^h = \alpha_2^h = \gamma_1^h = \gamma_2^h = 0 \qquad : \text{p-value= } 0.0172$$
$$Null: \alpha_1^h = \alpha_2^h = 0 \qquad : \text{p-value= } 0.0025$$
$$Null: \gamma_1^h = \gamma_2^h = 0 \qquad : \text{p-value= } 0.9006$$

Sub-sample l : t > t*, t*= 1991 q1

$$E(e_t^l Z_t) = E\{[R_t - \rho^l R_{t-1} - (1-\rho^l)(\theta^l + (\alpha_0^l + \alpha_1^l \delta_t + \alpha_2^l \delta_t^2)\pi_{t+k} + \beta^l y_{t+k} + (\gamma_0^l + \gamma_1^l \delta_t + \gamma_2^l \delta_t^2)s_t] Z_t\} = 0 \quad (42)$$

Table 4.9
Nonlinear model estimation result: Low inflation sub-period

	α_0	α_1	α_2	β	P	θ	γ_0	γ_1	γ_2	*J-statistic*
1991:2 – 2005:4	-0.904 (0.554)	0.389 (0.129)	0.107 (0.211)	-0.403 (0.434)	0.600 (0.159)	5.400 (1.472)	0.038 (0.022)	0.0002 (0.021)	0.012 (0.016)	5.570 [0.936]

Note that the nonlinearity tests are as follows:

$Null$: $\alpha_1^l = \alpha_2^l = \gamma_1^l = \gamma_2^l = 0$: p-value = 0.0000
$Null$: $\alpha_1^l = \alpha_2^l = 0$: p-value = 0.0002
$Null$: $\gamma_1^l = \gamma_2^l = 0$: p-value = 0.6075

4.5 Test of Structural Change

Carrying out the test of structural change by usual Wald-type coefficient stability test using dummy variables, we face short supply of IVs. That is, initially only 21 IVs are involved while there are 18 parameters in the general model of executing a structural break test. Here, the general model implies no constancy restrictions on any coefficient across sub-periods in the structural break test. So 21 IVs given 18 parameters imply too small a number to generate appropriate estimations in coefficients in over-identifying framework.[18] Extending IVs by adding more lag variables to existing IV set is essential. However, how many lag variables can be added? Upon Andrews (1999) methodology, broad recommendation about choosing number of IVs can be obtained. The main point of the methodology is exploiting trade-off relationships generated by *J-statistic* and number of over-identification. The basic trade-off relationships can be written as follows:

GMM-BIC(c) = $J_n(c) - (|c| - p)\ln n$: analogue of the BIC
where $J_n(c) =$ *J-statistic* and $(|c| - p) =$ *number of over-identification*

GMM-HQIC(c) = $J_n(c) - Q(|c| - p)\ln(\ln n)$: analogue of the HQIC
where $J_n(c) =$ *J-statistic*, $(|c| - p) =$ *number of over-identification*, and
Q is some number > 2

[18] In Clarida, Gali, and Gertler (2000), they use 20 IVs to estimate 5 coefficients and in Dupor and Conley (2004) they use 17 IVs to estimate 5 coefficients. So roughly they use 3~4 times more number of IVs than that of coefficients.

where $(|c| - p)\ln n$ and $Q(|c| - p)\ln(\ln n)$ are 'bonus terms' that "rewards selection vectors that utilize more moment conditions. This term is necessary to offset the increase in $J_n(c)$ that typically occurs when moment conditions are added," as Andrews (1999) points out. One thing to be mentioned here is that Andrews's methodology is not used to pick up the exact number of IVs. Rather, it is applied to grasp broad intuition of how many IVs can be added. Since the extension of numbers in IVs is done by adding a set of lag variables (i.e., six variables) one by one, whenever one lag variable is extended six more IVs increase at the same time.

For the general model, the above two criteria recommend roughly more than seven lags up to 14 lags IVs. Once over 14 lags IV, the criteria values show a sort of explosion. For the model with linear restriction on stock price gap coefficient, the criteria also recommend similar range. Considering both tests together, 12 lags IVs set case was picked as a representative, and the same structural break and nonlinearity tests were conducted for 10, 11, 13, and 14 lags cases. The three to five lags IV sets used in the previous section is definitely short for carrying out the test of structural change. The specific test results for choosing IVs are included in Appendix G.

Table 4.10 shows test results of structural change for the general model, i.e. using dummy variables for all coefficients. In the 12 lags IV set, 73 IVs, which is about four times more than 18, the number of coefficients, are involved and so there are 55 over-identifications. Test results illustrate two major findings. First, linearity of inflation and stock price gap coefficients are jointly rejected. In addition, most of nonlinearity power comes from inflation coefficients, which is consistent with the result in the analysis of the nonlinear model without considering structural change. Secondly, the usual joint Wald tests for coefficients' stability show that null hypotheses of 'no structural change' across sub-periods are rejected. That is, there can be a structural change with quite high probability given existence of nonlinearity in the coefficients. Tests of structural change were conducted for several coefficient sets such as set of all, set of inflation and stock price gap, and set of inflation and stock price gap coefficients respectively. For all cases, the null of no structural change is rejected. As mentioned, in choosing IVs, the same tests were conducted for 10, 11, 13, and 14 lags IVs cases, and similar and consistent results obtained in the12 lags IVs case with some variations. (See Appendix H)

General Model

$$\begin{aligned} E(e_t Z_t) = E\{[R_t - \rho D_1 R_{t-1} - (1-\rho D_1)\{D_1\theta + (\alpha_0 + \alpha_1\delta_t + \alpha_2\delta_t^2)D_1\pi_{t+k} + \beta D_1 y_{t+k} \\ + (\gamma_0 + \gamma_1\delta_t + \gamma_2\delta_t^2)D_1 s_t\} - \rho D_2 R_{t-1} - (1-\rho D_2)\{D_2\theta + (\alpha_0 + \alpha_1\delta_t + \alpha_2\delta_t^2)D_2\pi_{t+k} \\ + \beta D_2 y_{t+k} + (\gamma_0 + \gamma_1\delta_t + \gamma_2\delta_t^2)D_2 s_t]\, Z_t\} = 0 \end{aligned} \tag{43}$$

$$\text{where } D_1 = \begin{cases} 1 \; if \; t \le q1\,1991 \\ 0 \; if \; t > q2\,1991 \end{cases} \quad D_2 = \begin{cases} 0 \; if \; t \le q1\,1991 \\ 1 \; if \; t > q1\,1991 \end{cases}$$

Table 4.10
Test of structural change: General model

	α_0	α_1	α_2	β	ρ	θ	γ_0	γ_1	γ_2	*J-statistic*
1979:4 – 1991:1	1.208 (0.084)	0.251 (0.019)	0.004 (0.003)	0.082 (0.119)	0.539 (0.036)	4.697 (0.379)	-0.019 (0.007)	0.003 (0.005)	0.002 (0.002)	26.847 [0.9995]
1991:2 – 2005:4	2.356 (1.875)	0.437 (0.137)	-0.441 (0.240)	-0.363 (0.370)	0.793 (0.113)	-0.830 (4.290)	0.068 (0.040)	0.029 (0.028)	0.025 (0.018)	

Note that the nonlinearity tests are as follows:

Null: $\alpha_1^h = \alpha_2^h = \alpha_1^l = \alpha_2^l = \gamma_1^h = \gamma_2^h = \gamma_1^l = \gamma_2^l = 0$: p-value = 0.0000

Null: $\alpha_1^h = \alpha_1^l = \alpha_2^h = \alpha_2^l = 0$: p-value = 0.0000

Null: $\gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.4561

Wald tests for stability of coefficients are as follows:

Null: $\alpha_0^h = \alpha_0^l, \alpha_1^h = \alpha_1^l, \alpha_2^h = \alpha_2^l, \beta^h = \beta^l, \rho^h = \rho^l, \theta^h = \theta^l, \gamma_0^h = \gamma_0^l, \gamma_1^h = \gamma_1^l, \gamma_2^h = \gamma_2^l$:p-value = 0.0000

Null: $\alpha_0^h = \alpha_0^l, \alpha_1^h = \alpha_1^l, \alpha_2^h = \alpha_2^l, \gamma_0^h = \gamma_0^l, \gamma_1^h = \gamma_1^l, \gamma_2^h = \gamma_2^l \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l$:p-value = 0.0000

Null: $\alpha_0^h = \alpha_0^l, \alpha_1^h = \alpha_1^l, \alpha_2^h = \alpha_2^l \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l$: p-value = 0.0168

Null: $\gamma_0^h = \gamma_0^l, \gamma_1^h = \gamma_1^l, \gamma_2^h = \gamma_2^l \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l$: p-value = 0.0002

When drawing time-varying coefficients movements, there is somewhat different impression between inflation and stock price gap coefficients despite their common property containing statistical structural changes. When looking at Figure 4.4 for the inflation coefficient, nonlinearity appears to play quite an important role or dominance over structural break. That is, Fed seems to have responded to expected inflation pressure nonlinearly in a qualitative sense across sub-periods. The fact that most values of the inflation coefficient fall on greater than one indicates that across the sub-periods Fed's response is aggressive and significant given quantitative differences in magnitudes, which generates statistical structural change. This explanation is also consistent with the finding that most of nonlinearity power comes from the inflation coefficients.

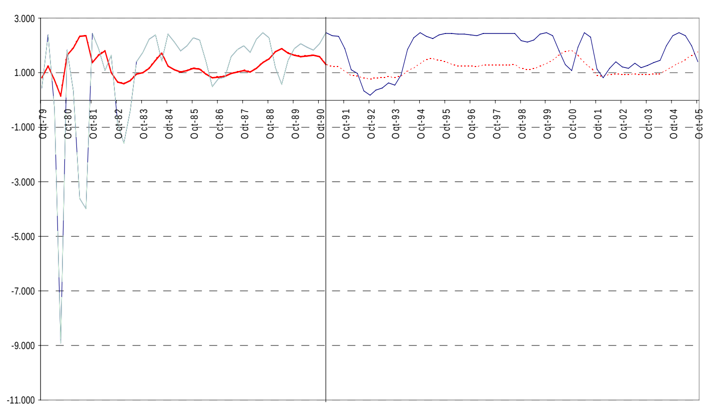

Fig. 4.4. Inflation coefficient movement: General model

Meanwhile, structural break in stock price gap coefficient looks dominant just like the test results in both the quality and quantity sense as shown in Figure 4.5. In the high inflation sub-period, most values of the coefficient are small and negative closing to zero. However, in the low inflation sub-period, the values are much larger and positive. The movements confirm the Dupor and Conley's (1994) argument in the nonlinear framework.

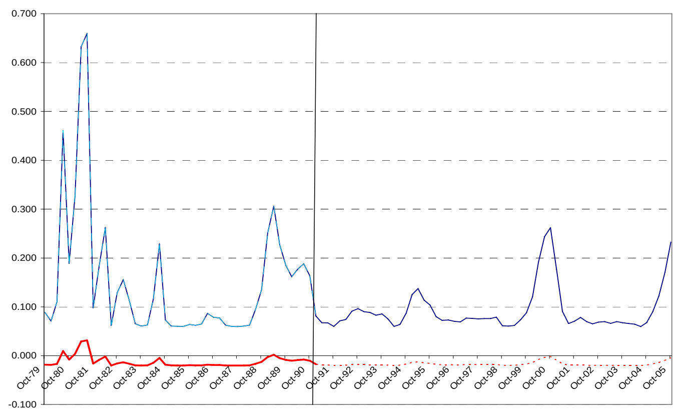

Fig. 4.5. Stock variable coefficient movement: General model

Since the stock price gap coefficient cannot generate nonlinearity by itself, tests of structural change were conducted with linear restriction on the stock variable coefficient. The test results, both of linearity and stability of coefficients, are similar to those of the general model. These results are displayed in Table 4.11.

Linear Restriction on Stock Price Gap Coefficient

$$\begin{aligned}E(e_t Z_t) = E\{[&R_t - \rho D_1 R_{t-1} - (1-\rho D_1)\{D_1\theta + (\alpha_0 + \alpha_1\delta_t + \alpha_2\delta_t^2)D_1\pi_{t+k} + \beta D_1 y_{t+k} \\ &+ \gamma_0 D_1 s_t\} - \rho D_2 R_{t-1} - (1-\rho D_2)\{D_2\theta + (\alpha_0 + \alpha_1\delta_t + \alpha_2\delta_t^2)D_2\pi_{t+k} + \beta D_2 y_{t+k} \\ &+ \gamma_0 D_2 s_t]\, Z_t\} = 0\end{aligned} \qquad (44)$$

where $D_1 = \begin{cases} 1\ if\ t \le q1\,1991 \\ 0\ if\ t > q2\,1991 \end{cases}$ $\quad D_2 = \begin{cases} 0\ if\ t \le q1\,1991 \\ 1\ if\ t > q1\,1991 \end{cases}$

Table 4.11
Test of structural change: Linear restriction on stock variable

	α_0	α_1	α_2	β	ρ	θ	γ_0	*J-statistic*
1979:4 – 1991:1	1.263 (0.068)	0.251 (0.020)	0.002 (0.002)	0.129 (0.108)	0.547 (0.035)	4.475 (0.336)	-0.017 (0.005)	28.55 [0.9997]
1991:2 – 2005:4	1.442 (0.879)	0.471 (0.079)	-0.228 (0.105)	-0.359 (0.260)	0.740 (0.066)	0.949 (1.786)	0.065 (0.012)	

Note that the nonlinearity tests are as follows.

Null: $\alpha_1^h = \alpha_2^h = \alpha_1^l = \alpha_2^l = 0 \,|\, \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l, \gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.0000

Null: $\alpha_1^h = \alpha_2^h = 0 \,|\, \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l, \gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.0000

Null: $\alpha_1^l = \alpha_2^l = 0 \,|\, \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l, \gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.0000

The Wald test for stability of coefficients are as follows.

Null: $\alpha_0^h = \alpha_0^l, \alpha_1^h = \alpha_1^l, \alpha_2^h = \alpha_2^l, \beta^h = \beta^l, \rho^h = \rho^l, \theta^h = \theta^l, \gamma_0^h = \gamma_0^l \,|\, \gamma_1^h = \gamma_2^h = \gamma_1^l = \gamma_2^l = 0$:p-value = 0.0000

Null: $\alpha_0^h = \alpha_0^l, \alpha_1^h = \alpha_1^l, \alpha_2^h = \alpha_2^l, \gamma_0^h = \gamma_0^l \,|\, \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l, \gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.0000

Null: $\alpha_0^h = \alpha_0^l, \alpha_1^h = \alpha_1^l, \alpha_2^h = \alpha_2^l \,|\, \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l, \gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.0000

Null: $\gamma_0^h = \gamma_0^l \,|\, \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l, \gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.0000

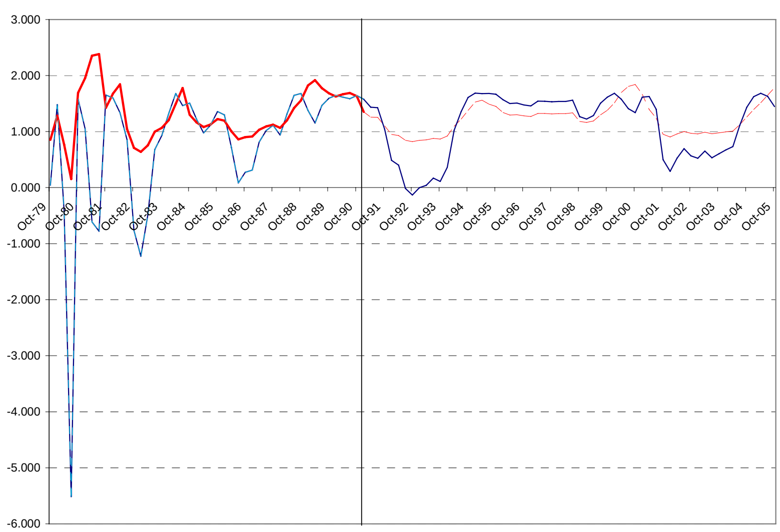

Fig. 4.6. Inflation coefficient movement: Linear restriction on stock variable.

Again, when looking at time-varying movements of inflation coefficient in Figure 4.6, the nonlinearity plays an important role in Fed's response to the expected inflation pressure. A small difference from the previous graph of the general model is two times the deviations from aggressive response in the low inflation sub-periods of the early 1990s and early 2000s, which periods are 1991-1992 recession in the U.S. economy and fallout period after the collapse of the dotcom bubble respectively.

4.6 Concluding Remarks

There are many issues in looking at the Fed's behaviors across the high and low inflation sub-periods. When the non-robustness of linear set-up around a breakpoint is verified, a nonlinear model is constructed as an alternative. Upon the nonlinear framework, identification of the dominant cause of apparent change in Fed behavior, between structural change and nonlinearity, is sought. The estimation results indicate that both nonlinearity and structural change matter in accounting for Fed's behaviors.

Through the coefficient movements, the weights of those two factors - nonlinearity and structural change - are somewhat different. For the inflation coefficient, Fed has responded to expected inflation pressure nonlinearly and aggressively for the entire sample period given statistical structural changes around the early 1990s. For the stock variable coefficient, Fed may change its position apparently, i.e. by more actively responding to non-fundamental stock price movements than before. This explanation is consistent with the test results indicating that most source of nonlinearity comes from inflation coefficients.

CHAPTER V

CONCLUSIONS

The superior performance of using the steady state BVAR (SS BVAR) in out-of-sample forecasts, especially for the long horizons, is demonstrated. Based on SS BVAR, the identification issue is explored through two different approaches; an economic theory and algorithms of inductive causation method called "DAGs". While the housing sector's specification is somewhat similar across various identification designs, the other exogenous status of other variables are quite different.

Once the system is identified, the main question is how the monetary policy shocks can affect the housing sector. Estimation results of impulse response of housing price and investment to FFRs in alternative identifications verify that the magnitudes are relatively smaller, less significant and shorter when compared to Choleski case. Also, this finding can be confirmed by historical decomposition and conditional forecast analyses. The recent high peak of housing prices cannot be well accounted for without feeding the housing prices' own shocks in the historical decomposition. Also, generated conditional forecasts of housing prices fail in replicating the run-up of housing prices around 2005, given the assumption that we had known the actual paths of real GDP (*y*), inflation (*p*), money demand (*m*), 30-yr. mortgage rate (*mor30*) and actual or simulated FFRs. With all these estimation results, it is hard to agree with the argument that the considerable responsibility of the current housing boom and fallout is due to monetary policy shocks. Rather, this research indicates that there is still enormous uncertainty between monetary policy and housing prices. The institutional shocks such as the fundamental change of mortgage markets including the securitizing mortgage debts could be one source of uncertainty.

There are many issues to consider in looking at the Fed's behaviors across the high and low inflation sub-periods. After relaxing the problem of non-robustness in the linear set-up around breakpoint with nonlinear model, the identification of the dominant cause of apparent change in the Fed behavior, between structural change and nonlinearity, is explored. The estimation results imply that considering both nonlinearity and structural change matter in accounting for the Fed's behavior. For the inflation coefficient, the Fed has responded to expected inflation pressure nonlinearly and aggressively for the entire sample period given structural change around the early 1990s. For the stock price coefficient, the Fed changes its position more clearly, i.e., more actively responding to non-fundamental stock price movements than before.

The dynamic relationship between monetary policy and asset prices needs further research when compared to relatively abundant research about the relationship between output or inflation and monetary policy. The relationship between the housing sector and macroeconomic variables including monetary policy is still a looming question.

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APPENDIX A

PROOF OF POSTERIOR DENSITY

Full conditional posterior of Σ

$$p(\Sigma \mid \Pi, \Psi, I_t) \sim IW(E'E, T)$$

This comes from usual standard Bayesian results.

Full conditional posterior of Π

$$p(vec\Pi \mid \Sigma, \Psi, I_t) \sim N_{kp^2}(\bar{\theta}_\Pi, \bar{\Omega}_\Pi)$$

Model $Y = X\Pi + E$ where Y is $(T\times p)$, X is $(T\times pk)$, Π is $(pk\times p)$, and E is $(T\times p)$.

(Proof)

$$p(I_T \mid \Sigma, vec\Pi, vec\Psi) = |\Sigma|^{-\frac{T}{2}} \exp[-\frac{1}{2} tr\{(Y - X\Pi)'(Y - X\Pi)\Sigma^{-1}\}]$$

$p(\Sigma, vec\Pi, vec\Psi \mid I_t) = p(\Sigma, vec\Pi, vec\Psi)\, p(I_T \mid \Sigma, vec\Pi, vec\Psi)$ by Bayes' Theorem

$= p(vec\Pi)\, p(vec\Psi)\, p(\Sigma)\, p(I_T \mid \Sigma, vec\Pi, vec\Psi)$ by independence of Π *and* Ψ and Σ is constant with respect to Π *and* Ψ

$\propto p(\Sigma)\, p(vec\Pi)\, p(I_T \mid \Sigma, vec\Pi, vec\Psi)$

$$= |\Sigma|^{-(p+1)/2} |\Omega_\Pi|^{-1/2} \exp[-\frac{1}{2}(vec\Pi - vec\theta_\Pi)'\Omega_\Pi^{-1}(vec\Pi - vec\theta_\Pi)]\, |\Sigma|^{-T/2} \exp[-\frac{1}{2} tr\{(Y - X\Pi)'(Y - X\Pi)\Sigma^{-1}\}]$$

by using priors and likelihood function

$$\propto \exp[-\frac{1}{2}(vec\Pi - vec\theta_\Pi)'\Omega_\Pi^{-1}(vec\Pi - vec\theta_\Pi) - \frac{1}{2} tr\{(Y - X\Pi)'(Y - X\Pi)\Sigma^{-1}\}]$$

where

$$(Y - X\Pi)'(Y - X\Pi) = (Y - X\bar{\theta}_\Pi - X(\Pi - \bar{\theta}))'(Y - X\bar{\theta}_\Pi - X(\Pi - \bar{\theta}_\Pi))$$

$$= (Y - X\bar{\theta}_\Pi)'(Y - X\bar{\theta}_\Pi) - (\Pi - \bar{\theta}_\Pi)'X'(Y - X\bar{\theta}_\Pi)$$

$$-(Y - X\bar{\theta}_\Pi)'X(\Pi - \bar{\theta}_\Pi) + (\Pi - \bar{\theta}_\Pi)'X'X(\Pi - \bar{\theta}_\Pi)$$

$$= S_1^* + C + C' + (\Pi - \bar{\theta}_\Pi)'X'X(\Pi - \bar{\theta}_\Pi)$$

where $S_1^* = (Y - X\bar{\theta}_\Pi)'(Y - X\bar{\theta}_\Pi)$

$C = -(\Pi - \bar{\theta}_\Pi)'X'(Y - X\bar{\theta}_\Pi)$

Thus

$$tr\{(Y - X\Pi)'(Y - X\Pi)\Sigma^{-1}\} = tr(S_1^*\Sigma^{-1}) + tr\{(\Pi - \bar{\theta}_\Pi)'X'X(\Pi - \bar{\theta}_\Pi)\Sigma^{-1}\} + tr\{(C + C')\Sigma^{-1}\}$$

where $tr\{(\Pi - \bar{\theta}_\Pi)'X'X(\Pi - \bar{\theta}_\Pi)\Sigma^{-1}\} = \{vec(X'X(\Pi - \bar{\theta}_\Pi))\}'vec\{(\Pi - \bar{\theta}_\Pi)\Sigma^{-1}\}$

since $tr(A'B) = \{vec(A)\}'vec(B)$ *and* $A = X'X(\Pi - \bar{\theta}_\Pi),\ B = (\Pi - \bar{\theta}_\Pi)\Sigma^{-1}$

$$= \{(I \otimes X'X)vec(\Pi - \bar{\theta}_\Pi)\}'(\Sigma^{-1} \otimes I)vec(\Pi - \bar{\theta}_\Pi)$$

since $vec(AB) = (I \otimes A)vec(B) + (B' \otimes I)vec(A)$

$$= (vec\Pi - vec\bar{\theta}_\Pi)'(I \otimes X'X)(\Sigma^{-1} \otimes I)(vec\Pi - vec\bar{\theta}_\Pi)$$

$$= (vec\Pi - vec\bar{\theta}_\Pi)'(\Sigma^{-1} \otimes X'X)(vec\Pi - vec\bar{\theta}_\Pi)$$

Also Note that

$$(vec\Pi - vec\theta_\Pi)'\Omega_\Pi^{-1}(vec\Pi - vec\theta_\Pi)$$

$$\equiv \{(vec\Pi - vec\bar{\theta}_\Pi) - (vec\theta_\Pi - vec\bar{\theta}_\Pi)\}'\Omega_\Pi^{-1}\{(vec\Pi - vec\bar{\theta}_\Pi) - (vec\theta_\Pi - vec\bar{\theta}_\Pi)\}$$

$$= (vec\Pi - vec\bar{\theta}_\Pi)'\Omega_\Pi^{-1}(vec\Pi - vec\bar{\theta}_\Pi) - (vec\Pi - vec\bar{\theta}_\Pi)'\Omega_\Pi^{-1}(vec\theta_\Pi - vec\bar{\theta}_\Pi)$$

$$- (vec\theta_\Pi - vec\bar{\theta}_\Pi)'\Omega_\Pi^{-1}(vec\Pi - vec\bar{\theta}_\Pi) + (vec\Pi - vec\bar{\theta}_\Pi)'\Omega_\Pi^{-1}(vec\theta_\Pi - vec\bar{\theta}_\Pi)$$

$$= S_2^* + (vec\Pi - vec\bar{\theta}_\Pi)'\Omega_\Pi^{-1}(vec\theta_\Pi - vec\bar{\theta}_\Pi) - D - D'$$

where

$$S_2^* = (vec\theta_\Pi - vec\bar{\theta}_\Pi)'\Omega_\Pi^{-1}(vec\theta_\Pi - vec\bar{\theta}_\Pi)$$

$$D = (vec\Pi - vec\bar{\theta}_\Pi)'\Omega_\Pi^{-1}(vec\theta_\Pi - vec\bar{\theta}_\Pi)$$

Thus

$$p(vec\Pi, \Sigma, vec\Psi \mid I_T) \propto \exp[-\frac{1}{2}\{tr(S_1^*\Sigma^{-1}) - tr(C + C')\Sigma^{-1} + S_2^* - D - D' + (vec\Pi - vec\bar{\theta}_\Pi)'(\Sigma^{-1} \otimes X'X)$$

$$(vec\Pi - vec\theta_\Pi) - (vec\Pi - vec\bar{\theta}_\Pi)'\Omega_\Pi^{-1}(vec\Pi - vec\bar{\theta}_\Pi)\}]$$

$$= \exp[-\frac{1}{2}\{tr(S_1^*\Sigma^{-1}) - tr(C + C')\Sigma^{-1} + S_2^* - D - D' + (vec\Pi - vec\bar{\theta}_\Pi)'(\Sigma^{-1} \otimes X'X + \Omega_\Pi^{-1})(vec\Pi - vec\bar{\theta}_\Pi)\}]$$

So

$$p(vec\Pi \mid \Sigma, vec\Psi, I_T) \propto \exp[-\frac{1}{2}\{-tr(C+C')\Sigma^{-1} - D - D' + (vec\Pi - vec\bar{\theta}_\Pi)'(\Sigma^{-1}\otimes X'X + \Omega_\Pi^{-1})(vec\Pi - vec\bar{\theta}_\Pi)\}]$$

since S_1^* and S_2^* are constants given Σ

Now let's check $tr(C\Sigma^{-1}) + D$

$$tr(C\Sigma^{-1}) + D = tr\{(\Pi - \bar{\theta}_\Pi)'X'(Y - X\bar{\theta}_\Pi)\Sigma^{-1}\} + (vec\Pi - vec\bar{\theta}_\Pi)'\Omega_\Pi^{-1}(vec\theta_\Pi - vec\bar{\theta}_\Pi)$$

where

$$\begin{aligned}
tr(C\Sigma^{-1}) &= tr\{(\Pi - \bar{\theta}_\Pi)'X'(Y - X\bar{\theta}_\Pi)\Sigma^{-1}\} \\
&= \{vec(X(\Pi - \bar{\theta}_\Pi)\}'vec\{(Y - X\bar{\theta}_\Pi)\Sigma^{-1}\} \\
&= \{(I\otimes X)vec(\Pi - \bar{\theta}_\Pi)\}'(\Sigma^{-1}\otimes I)vec(Y - X\bar{\theta}_\Pi) \\
&= (vec\Pi - vec\bar{\theta}_\Pi)'(I\otimes X)(\Sigma^{-1}\otimes I)vec(Y - X\bar{\theta}_\Pi) \\
&= (vec\Pi - vec\bar{\theta}_\Pi)'(\Sigma^{-1}\otimes X)(vecY - vec(X\bar{\theta}_\Pi))
\end{aligned}$$

Thus

$$tr(C\Sigma^{-1}) + D = (vec\Pi - vec\bar{\theta}_\Pi)'\{(\Sigma^{-1}\otimes X')(vecY - vec(X\bar{\theta}_\Pi)) + \Omega_\Pi^{-1}(vec\theta_\Pi - vec\bar{\theta}_\Pi)\}$$

Pick $\bar{\theta}_\Pi$ such that { } to be zero

$$\begin{aligned}
&\{(\Sigma^{-1}\otimes X')(vecY - vec(X\bar{\theta}_\Pi)) + \Omega_\Pi^{-1}(vec\theta_\Pi - vec\bar{\theta}_\Pi)\} = 0 \\
&(\Sigma^{-1}\otimes X')(vecY - (I\otimes X)vec(\bar{\theta}_\Pi)) + \Omega_\Pi^{-1}(vec\theta_\Pi - vec\bar{\theta}_\Pi) = 0 \\
&(\Sigma^{-1}\otimes X')vecY - (\Sigma^{-1}\otimes X'X)vec(\bar{\theta}_\Pi) + \Omega_\Pi^{-1}vec\theta_\Pi - \Omega_\Pi^{-1}vec\bar{\theta}_\Pi = 0 \\
&\{(\Sigma^{-1}\otimes X'X) + \Omega_\Pi^{-1}\}vec\theta_\Pi = (\Sigma^{-1}\otimes X')vecY + \Omega_\Pi^{-1}vec\theta_\Pi
\end{aligned}$$

Therefore

$$\begin{aligned}
vec\bar{\theta}_\Pi &= \{(\Sigma^{-1}\otimes X'X) + \Omega_\Pi^{-1}\}^{-1}\{(\Sigma^{-1}\otimes X')vecY + \Omega_\Pi^{-1}vec\theta_\Pi\} \\
&= \{(\Sigma^{-1}\otimes X'X) + \Omega_\Pi^{-1}\}^{-1}\{vec(X'Y\Sigma^{-1}) + \Omega_\Pi^{-1}vec\theta_\Pi\}
\end{aligned}$$

where

$$\begin{aligned}
(\Sigma^{-1}\otimes X')vecY &= (I\otimes X')vec(Y\Sigma^{-1}) \\
&= (I\otimes X')(\Sigma^{-1}\otimes I)vecY \\
&= (\Sigma^{-1}\otimes X')vecY
\end{aligned}$$

Finally

$$p(vec\Pi \mid \Sigma, vec\Psi, I_T) \propto \exp[-\frac{1}{2}\{(vec\Pi - vec\bar{\theta}_\Pi)'(\Sigma^{-1}\otimes X'X + \Omega_\Pi^{-1})(vec\Pi - vec\bar{\theta}_\Pi)\}]$$

where $vec\bar{\theta}_\Pi = \bar{\Omega}_\Pi^{-1}\{vec(X'Y\Sigma^{-1}) + \Omega_\Pi^{-1}vec\theta_\Pi\}$

and $\bar{\Omega}_\Pi = \Sigma^{-1}\otimes X'X + +\Omega_\Pi^{-1}$

Full conditional posterior of $\bar{\Psi}$

$$p(vec\Psi \mid \Sigma, \Pi, I_t) \sim N_{pq}(\bar{\theta}_\Psi, \bar{\Omega}_\Psi)$$

(proof)

Let $vec(\Theta') \equiv vec(\Psi, \Pi_1\Psi, ..., \Pi_k\Psi) = \begin{pmatrix} I_p \\ I_p \otimes \Pi_1 \\ \dots \\ I_p \otimes \Pi_k \end{pmatrix} vec(\Psi) = U\, vec(\Psi)$

Thus I can rewrite the original equation as follows.

$Y = D\Theta + E$, where $E = (\varepsilon_1, \varepsilon_2, \dots, \varepsilon_p)$

$(T \times p)$ matrix of unobserved random disturbance terms.
I assume that the rows of *E* are independently distributed, each with a *p*-dimensional normal distribution with zero vector mean and positive definite $p\times p$ covariance matrix Σ.

$$p(Y, D \mid \Sigma, \Pi, \Psi) = |\Sigma|^{-T/2} \exp[-\frac{1}{2} tr\{(Y - D\Theta)'(Y - D\Theta)\Sigma^{-1}\}]$$

by definition of likelihood function

$$\propto \exp[-\frac{1}{2} tr\{(Y - D\Theta)'(Y - D\Theta)\Sigma^{-1}\}]$$

$$= \exp[-\frac{1}{2} tr\{\Sigma^{-1}(Y - D\Theta)'(Y - D\Theta)\}] \quad \text{since tr(AB)=tr(BA)}$$

$$= \exp[-\frac{1}{2} tr\{\Sigma^{-1}(Y - D\hat{\Theta} - D(\Theta - \hat{\Theta}))'(Y - D\hat{\Theta} - D(\Theta - \hat{\Theta})\}]$$

where $\hat{\Theta} = (D'D)^{-1}D'Y$

$$= \exp[-\frac{1}{2} tr\{\Sigma^{-1}((Y - D\hat{\Theta})'(Y - D\hat{\Theta}) + (\Theta - \hat{\Theta})'D'D(\Theta - \hat{\Theta})\}]$$

since $(\Theta - \hat{\Theta})'D'(Y - D\hat{\Theta}) = (\Theta - \hat{\Theta})'(D'Y - D'D\hat{\Theta})$

$$= (\Theta - \hat{\Theta})'(D'Y - D'D(D'D)^{-1}D'Y)$$

$$= 0$$

$$= \exp[S_1^* - \frac{1}{2} tr\{\Sigma^{-1}(\Theta - \hat{\Theta})'D'D(\Theta - \hat{\Theta})\}]$$

where $S_1^* = -\frac{1}{2} tr\{\Sigma^{-1}(Y - D\hat{\Theta})'(Y - D\hat{\Theta})\}$

$$= \exp[S_1^* - \frac{1}{2} tr\{(\Theta' - \hat{\Theta}')'\Sigma^{-1}(\Theta' - \hat{\Theta}')D'D\}]$$

since tr(AB)=tr(BA), where

$A = \Sigma^{-1}(\Theta - \hat{\Theta})'D'D,\ B = (\Theta - \hat{\Theta})\}]$

$$= \exp[S_1^* - \frac{1}{2} tr\{(\Sigma^{-1}(\Theta' - \hat{\Theta}'))'(\Theta' - \hat{\Theta}')D'D\}]$$

$$= \exp[S_1^* - \frac{1}{2}\{vec(\Sigma^{-1}(\Theta' - \hat{\Theta}')\}'vec\{(\Theta' - \hat{\Theta}')D'D\}]$$

since $tr(A'B) = \{vec(A)\}'vec(B)$ where

$A = \Sigma^{-1}(\Theta - \hat{\Theta})',\ B = (\Theta' - \hat{\Theta}')D'D$

$$= \exp[S_1^* - \frac{1}{2}\{I_p \otimes \Sigma^{-1} vec(\Theta' - \hat{\Theta}')\}'\{D'D \otimes I_p vec(\Theta' - \hat{\Theta}')\}]$$

since $vec(AB) = (I \otimes A)vec(B) = (B' \otimes I)vec(A)$

$$= \exp[S_1^* - \frac{1}{2}\{vec(\Theta' - \hat{\Theta}')\}'(I_p \otimes \Sigma^{-1})(D'D \otimes I_p)vec(\Theta' - \hat{\Theta}')]$$

since $(A \otimes B)' = (A' \otimes B')$

$$= \exp[S_1^* - \frac{1}{2}(Uvec\Psi - vec\hat{\Theta}')'(D'D \otimes \Sigma^{-1})(Uvec\Psi - vec\hat{\Theta}')]$$

since $vec(\Theta') = Uvec\Psi,\ (A \otimes B)(C \otimes D) = AC \otimes BD$

$$= \exp[S_1^* - \frac{1}{2}\{(vec\Psi)'U' - (vec\hat{\Theta}')'\}(D'D \otimes \Sigma^{-1})(Uvec\Psi - vec\hat{\Theta}')]$$

$$= \exp[S_1^* - \frac{1}{2}\{(vec\Psi)'U'(D'D \otimes \Sigma^{-1})Uvec\Psi - (vec\Psi)'U'(D'D \otimes \Sigma^{-1})vec\hat{\Theta}'$$

$$- (vec\hat{\Theta}')'(D'D \otimes \Sigma^{-1})Uvec\Psi + (vec\hat{\Theta}')'(D'D \otimes \Sigma^{-1})vec\hat{\Theta}']$$

$$= \exp[S_1^* - \frac{1}{2}\{(vec\Psi)'Avec\Psi - (vec\Psi)'B - B'vec\Psi + (vec\hat{\Theta}')'(D'D \otimes \Sigma^{-1})vec\hat{\Theta}'\}]$$

where $A = U'(D'D \otimes \Sigma^{-1})U,\ B = U'(D'D \otimes \Sigma^{-1})vec\hat{\Theta}'$

$$= \exp[S_1^* + S_2^* - \frac{1}{2}\{(vec\Psi)'Avec\Psi - (vec\Psi)'B - B'vec\Psi\}]$$

where $S_2^* = (vec\hat{\Theta}')'(D'D \otimes \Sigma^{-1})vec\hat{\Theta}'$

$$= \exp[S_1^* + S_2^* - \frac{1}{2}(\psi'A\psi - \psi'B - B'\psi)]$$

where $\psi = vec\Psi$

$$= \exp[S_1^* + S_2^* + S_3^* - \frac{1}{2}(\psi - \hat{\psi})' A(\psi - \hat{\psi})]$$

where $S_3^* = \hat{\psi}' A \hat{\psi}, \hat{\psi} = A^{-1}B$ note that $A\hat{\psi} = B, B' = \hat{\psi}' A' = \hat{\psi}' A$

$$= \exp[S_1^* + S_2^* + S_3^* - \frac{1}{2}(\psi - \hat{\psi})' A(\psi - \hat{\psi})]$$

Thus

$$p(Y, D \mid \Sigma, \Pi, \Psi) \propto \exp[S_1^* + S_2^* + S_3^* - \frac{1}{2}(\psi - \hat{\psi})' A(\psi - \hat{\psi})]$$

$p(\Psi, \Sigma, \Pi \mid Y, D) = p(\Psi, \Sigma, \Pi) p(Y, D \mid \Sigma, \Pi, \Psi)$ by Bayes' rule

$= p(\Psi) p(\Sigma) p(\Pi) p(Y, D \mid \Sigma, \Pi, \Psi)$ by independence

$\propto p(\Psi) p(Y, D \mid \Sigma, \Pi, \Psi)$

$$\propto \exp[-\frac{1}{2}(\Psi - \theta_\Psi)' \Omega_\Psi^{-1}(\Psi - \theta_\Psi) \exp[S_1^* + S_2^* + S_3^* - \frac{1}{2}(\psi - \hat{\psi})' A(\psi - \hat{\psi})]$$

$$= \exp[S_1^* + S_2^* + S_3^* - \frac{1}{2}\{(\Psi - \theta_\Psi)' \Omega_\Psi^{-1}(\Psi - \theta_\Psi) + (\psi - \hat{\psi})' A(\psi - \hat{\psi})\}]$$

$$= \exp[S_1^* + S_2^* + S_3^* - \frac{1}{2}\{(\Psi - \bar{\theta}_\Psi - (\theta_\Psi - \bar{\theta}_\Psi))' \Omega_\Psi^{-1}(\Psi - \bar{\theta}_\Psi - (\theta_\Psi - \bar{\theta}_\Psi))$$

$$+ (\psi - \bar{\theta}_\Psi - (\hat{\psi} - \bar{\theta}_\Psi))' A(\psi - \bar{\theta}_\Psi - (\hat{\psi} - \bar{\theta}_\Psi))\}]$$

$$= \exp[S_1^* + S_2^* + S_3^* + S_\Psi^* - \frac{1}{2}\{(\Psi - \bar{\theta}_\Psi)'(\Omega_\Psi^{-1} + A)(\Psi - \bar{\theta}_\Psi)\}]$$

where $S_\Psi^* = (\theta_\Psi - \bar{\theta}_\Psi)' \Omega_\Psi^{-1}(\theta_\Psi - \bar{\theta}_\Psi) + (\hat{\psi} - \bar{\theta}_\Psi)' A(\hat{\psi} - \bar{\theta}_\Psi)$

and given $(\psi - \bar{\theta}_\Psi)' \Omega_\Psi^{-1}(\theta_\Psi - \bar{\theta}_\Psi) + (\psi - \bar{\theta}_\Psi)' A(\hat{\psi} - \bar{\theta}_\Psi)$

$$= (\psi - \bar{\theta}_\Psi)' \{\Omega_\Psi^{-1}(\theta_\Psi - \bar{\theta}_\Psi) + A(\hat{\psi} - \bar{\theta}_\Psi)\}$$
$$= 0$$

Thus

$$\Omega_\Psi^{-1}(\theta_\Psi - \bar{\theta}_\Psi) + A(\hat{\psi} - \bar{\theta}_\Psi) = 0$$

$$\Omega_\Psi^{-1}\theta_\Psi - \Omega_\Psi^{-1}\bar{\theta}_\Psi + A\hat{\psi} - A\bar{\theta}_\Psi = 0$$

$$(\Omega_\Psi^{-1} + A)\bar{\theta}_\Psi = \Omega_\Psi^{-1}\theta_\Psi + A\hat{\psi}$$

Therefore $\bar{\theta}_\Psi = (\Omega_\Psi^{-1} + A)^{-1}(\Omega_\Psi^{-1}\theta_\Psi + A\hat{\psi})$

$$p(\Psi \mid \Sigma, \Pi, Y, D) \propto \exp[-\frac{1}{2}\{(\Psi - \bar{\theta}_\Psi)'(\Omega_\Psi^{-1} + A)(\Psi - \bar{\theta}_\Psi)\}]$$

since given $\Sigma, \Pi, Y, and\ D\ S_1^*, S_2^*, S_3^*, and\ S_\Psi^*$ are constant

$$\sim N_{pq}(\bar{\theta}_\Psi, (\Omega_\Psi^{-1} + A)^{-1})$$

where $A = U'(D'D \otimes \Sigma^{-1})U$

and also
$$\begin{aligned}\bar{\theta}_\Psi &= (\Omega_\Psi^{-1} + A)^{-1}(\Omega_\Psi^{-1}\theta_\Psi + A\hat{\psi}) \\ &= (\Omega_\Psi^{-1} + A)^{-1}(\Omega_\Psi^{-1}\theta_\Psi + AA^{-1}B) \\ &= (\Omega_\Psi^{-1} + A)^{-1}(\Omega_\Psi^{-1}\theta_\Psi + B) \\ &= (\Omega_\Psi^{-1} + A)^{-1}(\Omega_\Psi^{-1}\theta_\Psi + U'(D'D \otimes \Sigma^{-1})vec\,\hat{\Theta}')\end{aligned}$$

APPENDIX B

GENERATED DATA ILLUSTRATION

The model can be written as following equation (B.1).

$$\Pi(L)(x_t - \Psi d_t) = \varepsilon_t \tag{B.1}$$

where x_t is p-dimensional vector of time series at time t. d_t is q-dimensional vector of deterministic trends or other exogenous variables, $\Pi(L) = I_p - \Pi_1 L - \Pi_2 L^2 - \cdots - \Pi_k L^k$, $\Pi = (\Pi_1, ..., \Pi_k)'$, and $\varepsilon_t \sim N_p(0, \Sigma)$ and is independent between time periods. In this setup the unconditional mean of the process is directly specified by Ψ as $E_0(x_t) = \Psi d_t$.

Now a bi-variate time series of length 100 is generated from the stationary mean-adjusted VAR in (B.1) under following true values which constitute k = 1, d_t = 1, $\Psi' = (\psi_1, \psi_2) = (1, 4)$, $\Pi_1 = Diag(0.95, 0.95)$, and $\Sigma = Diag(0.1, 0.1)$. The system is close (or near) unit-root process as expressed in equation (B.2)

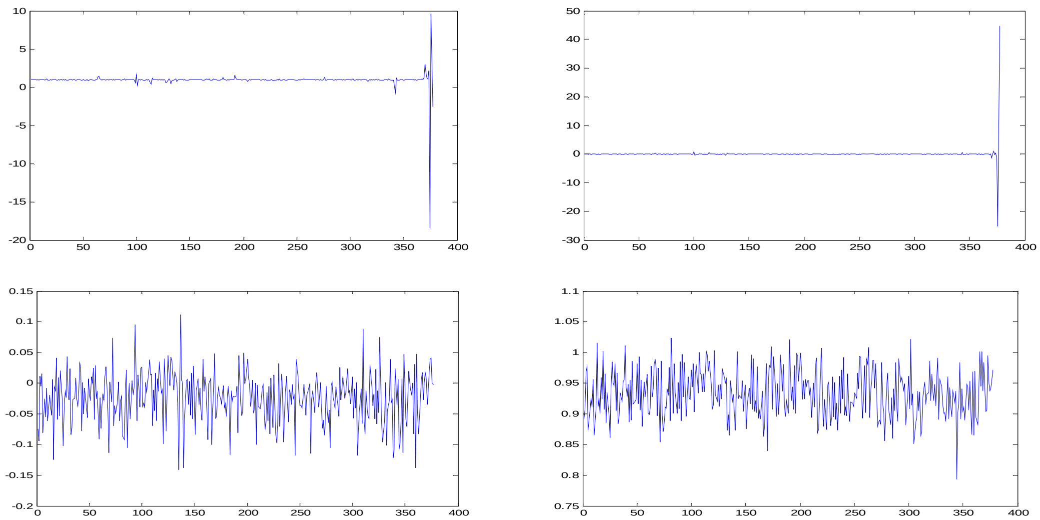
$$\begin{aligned} (x_{1t} - 1) &= 0.95 * (x_{1t-1} - 1) + \varepsilon_{1t} \\ (x_{2t} - 4) &= 0.95 * (x_{2t-1} - 4) + \varepsilon_{2t} \end{aligned} \tag{B.2}$$

I conduct three experiments of 2000 Gibbs sampling with a flat prior on Π_1, and diffuse prior ($|\Sigma|^{-(p+1)/2}$) on Σ: (1) Flat (non-informative) prior on steady state (Ψ), (2) Mildly informative prior on steady state (Ψ), (3) Fully informative prior on steady state (Ψ). As well illustrated in following graphs, even mildly informative prior on steady state plays a big role in converging the true parameters.

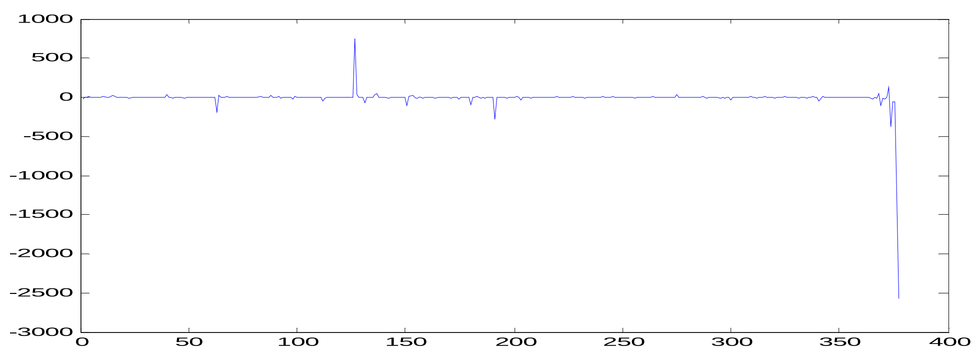
(1) Flat prior on steady state (Ψ) : non-informative case

I cannot keep sampling until 2000: caused by drawing from non-stationary region.

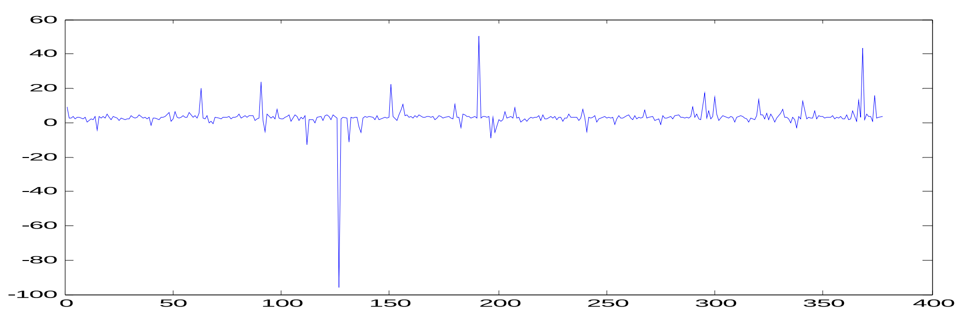
Π_1



ψ_1



ψ_2

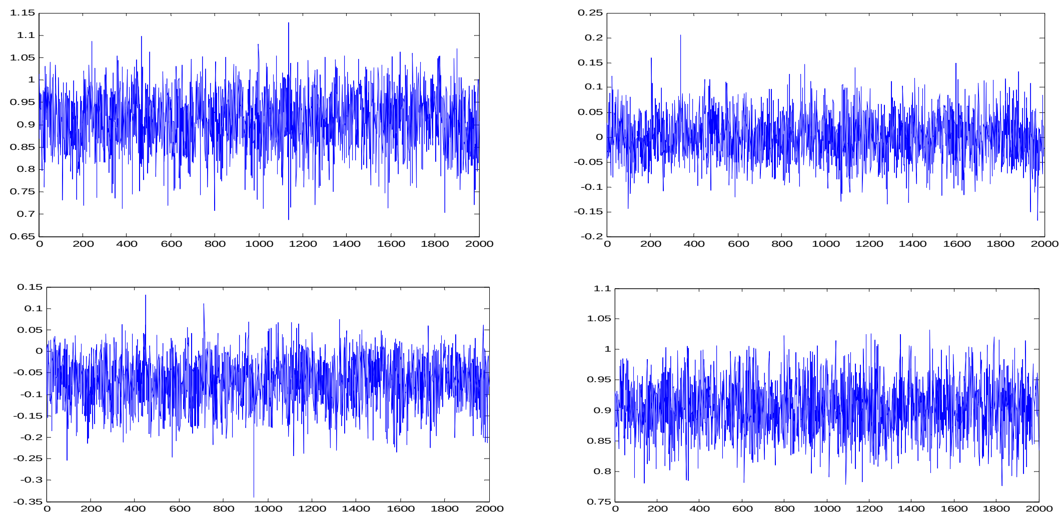


(2) Mildly informative prior on steady state (Ψ) : $\psi_1 \sim N(2.5, 1.25^2)$

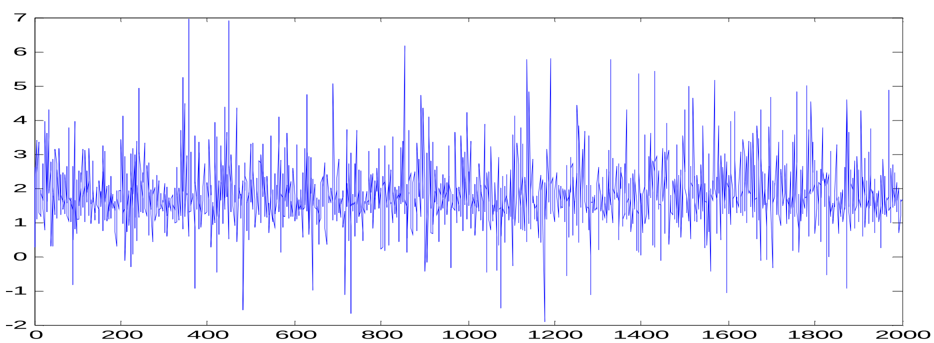
$\psi_2 \sim N(5, 2.5^2)$

ψ_1 *and* ψ_2 *are independent*

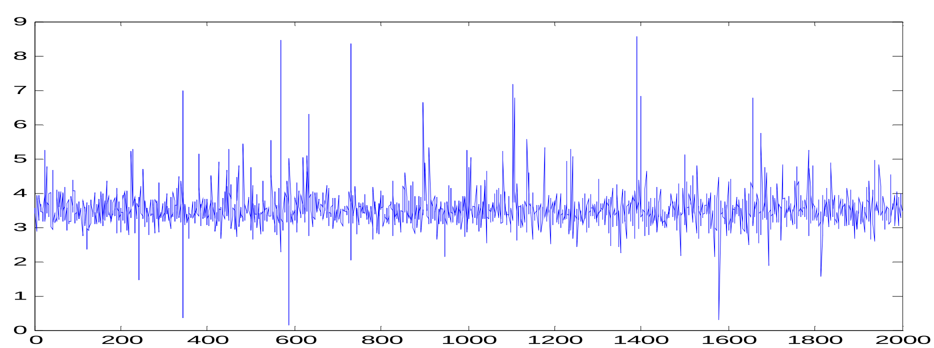
Π_1



$\psi_1 \sim N(2.5, 1.25^2)$



$\psi_2 \sim N(5, 2.5^2)$

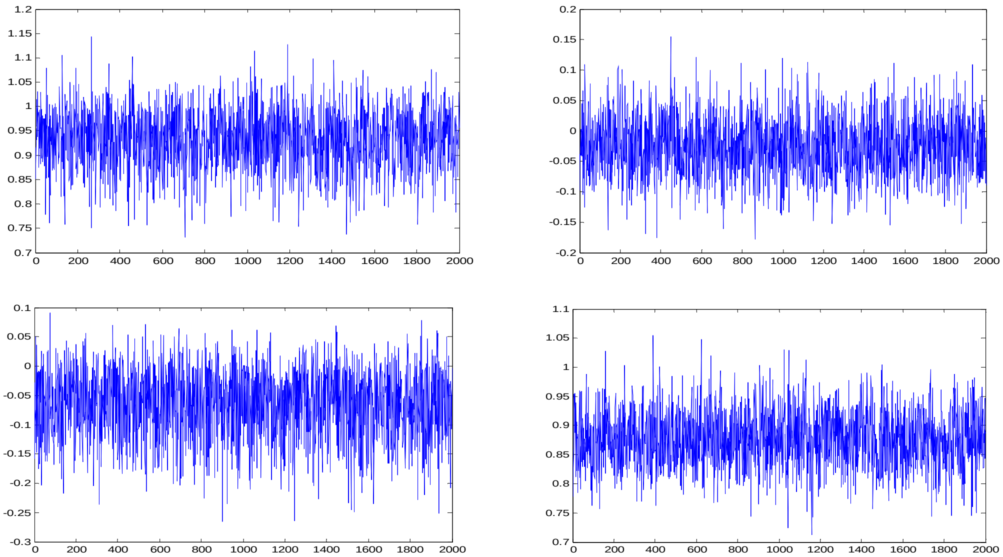


(3) Fully informative prior on steady state (Ψ): $\psi_1 \sim N(1, 1^2)$

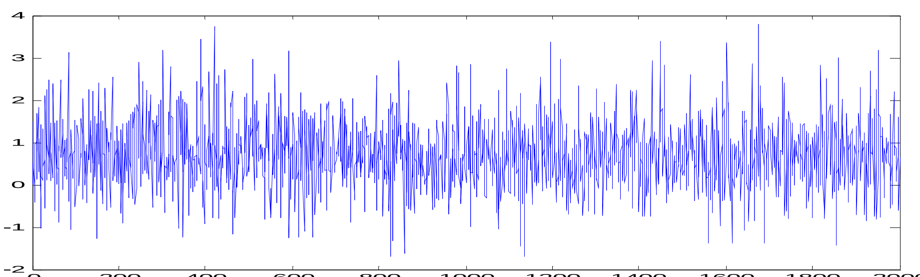
$\psi_2 \sim N(4, 1^2)$

ψ_1 *and* ψ_2 *are independent*

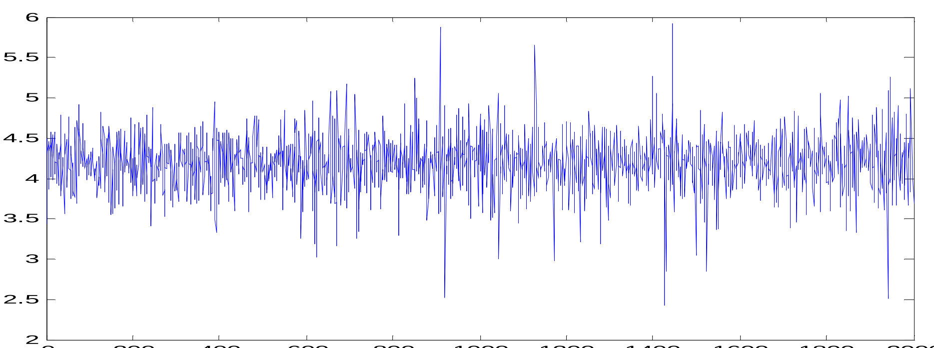
Π_1



$\psi_1 \sim N(1, 1^2)$



$\psi_2 \sim N(4, 1^2)$



APPENDIX C

ESTIMATION RESULTS OF CONTEMPORANEOUS MATRICES

(Gordon and Leeper (1994) + Housing Sector Specification)

	cp	*m*	*i*	*hp*	*hi*	*y*	*p*	*mor30*
cp	0.327 (0.020)	0	0	0	0	-0.210 (0.171)	-0.588 (0.484)	-0.987 (0.268)
MD	0	2.175 (0.280)	1.247 (0.396)	0	0	-0.519 (0.231)	-0.804 (0.479)	0
MS	-0.043 (0.029)	-1.116 (0.504)	1.738 (0.305)	0	0	0	0	-1.214 (0.314)
hp	0	0	0.084 (0.207)	2.143 (0.183)	11.261 (9.608)	-0.585 (0.200)	0	1.998 (0.316)
hi	0	0	0	-0.914 (0.273)	69.017 (4.586)	-0.807 (0.175)	-2.406 (0.561)	0
y	0	0	0	0	0	1.830 (0.117)	0	0
p	0	0	0	0	0	0.146 (0.165)	5.258 (0.335)	0
mor30	0	0	0	0	0	-0.455 (0.167)	-0.832 (0.479)	2.851 (0.182)

Note: Standard errors are in parentheses.

(Sims and Zha (2008) + Housing Sector Specification)

	cp	*m*	*i*	*hp*	*hi*	*y*	*p*	*mor30*
cp	0.057 (0.059)	1.214 (0.401)	0.876 (0.286)	0.416 (0.486)	-46.344 (11.141)	-0.694 (0.343)	0.065 (1.053)	1.188 (0.700)
MD	0	2.124 (0.333)	-0.576 (0.559)	0	0	0.468 (0.315)	-0.214 (0.593)	0
MS	-0.038 (0.042)	0.653 (0.479)	2.012 (0.190)	0	0	0	0	-1.937 (0.447)
hp	0.020 (0.036)	0	-0.225 (0.275)	-1.808 (0.272)	-25.908 (12.079)	1.063 (0.302)	0	-2.315 (0.415)
hi	0.043 (0.044)	0	0	-1.629 (0.248)	51.560 (10.703)	-1.062 (0.309)	-3.122 (0.702)	0
y	-0.228 (0.083)	0	0	0	0	-0.972 (0.664)	0	0
p	0.004 (0.061)	0	0	0	0	-0.204 (0.479)	5.154 (0.492)	0
mor30	-0.223 (0.079)	0	0	0	0	0.885 (0.423)	0.543 (1.089)	2.100 (0.605)

Note: Standard errors are in parentheses.

(PC Algorithm)

	cp	*m*	*i*	*hp*	*hi*	*y*	*p*	*mor30*
cp	0.300 (0.019)	0	0	0	0	0	0	0
MD	0	2.359 (0.153)	0	0	0	0	0	0
MS	0	0	2.094 (0.136)	0	0	0	0	-1.524 (0.269)
hp	0	0	0	2.406 (0.187)	-26.397 (10.091)	0	2.638 (0.529)	1.202 (0.499)
hi	0	-0.623 (0.215)	0	0.080 (0.348)	67.210 (6.020)	-0.850 (0.175)	-1.225 (0.655)	0
y	0	0	-0.855 (0.177)	0	0	2.000 (0.128)	0	0
p	0	0	0	0	0	0	5.242 (0.330)	0
mor30	-0.124 (0.028)	0	0	0.740 (0.333)	0	0	0	3.464 (0.265)

Note: Standard errors are in parentheses.

(GES Algorithm)

	cp	*m*	*i*	*hp*	*hi*	*y*	*p*	*mor30*
cp	0.300 (0.019)	0	0	0	0	0	0	0
MD	0	2.359 (0.150)	0	0	0	0	0	0
MS	0	0	2.094 (0.132)	0	0	0	0	-1.475 (0.263)
hp	0	0	0	2.275 (0.139)	-16.276 (5.407)	0	0	1.994 (0.274)
hi	0	-0.663 (0.217)	0	0	66.128 (4.189)	-0.759 (0.171)	0	0
y	0	0	-0.815 (0.173)	0	0	2.000 (0.127)	0	0
p	0	0	0	0.859 (0.174)	-25.043 (6.046)	0.406 (0.178)	6.009 (0.381)	0
mor30	0	0	0	0	0	0	0	2.742 (0.175)

Note: Standard errors are in parentheses.

APPENDIX D

BIVARIATE VAR(1) ILLUSTRATION FOR CONDITIONAL FORECAST

We can compute the multi step-ahead forecasts of *hp* (housing price) conditional on actual *i*(FFRs)'s path by restricting sequence of structural shock of *i*. For simplicity I just focus on one step-ahead forecast case. The structural and reduced form bivariate VAR(1), i.e., with one lag, can be written as:

$$By_t = B_1 y_{t-1} + e_t, \quad \text{where } \; e_t \sim N(0, I_2)$$
$$y_t = B^{-1}B_1 y_{t-1} + B^{-1}e_t$$

That is,

$$\begin{pmatrix} i \\ hp \end{pmatrix}_t = B^{-1}B_1 \begin{pmatrix} i \\ hp \end{pmatrix}_{t-1} + B^{-1}\begin{pmatrix} e^i \\ e^{hp} \end{pmatrix}_t \tag{D.1}$$

Let's assume $B^{-1}B_1 = A = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}$, $B = \begin{pmatrix} b_{11} & 0 \\ b_{21} & b_{22} \end{pmatrix}$, then $B^{-1} = \begin{pmatrix} b_{11}^{-1} & 0 \\ -b_{21}/b_{11}b_{22} & b_{22}^{-1} \end{pmatrix}$.

So equation (D.1) can be rewritten as follows.

$$\begin{pmatrix} i \\ hp \end{pmatrix}_t = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}\begin{pmatrix} i \\ hp \end{pmatrix}_{t-1} + \begin{pmatrix} b_{11}^{-1} & 0 \\ -b_{21}/b_{11}b_{22} & b_{22}^{-1} \end{pmatrix}\begin{pmatrix} e^i \\ e^{hp} \end{pmatrix}_t \tag{D.2}$$

Now one step-ahead (*S+1*) forecasts at time *S* can be produced using equation (D.2).

$$\begin{pmatrix} i \\ hp \end{pmatrix}_{S+1} = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}\begin{pmatrix} i \\ hp \end{pmatrix}_{S} + \begin{pmatrix} b_{11}^{-1} & 0 \\ -b_{21}/b_{11}b_{22} & b_{22}^{-1} \end{pmatrix}\begin{pmatrix} e^i \\ e^{hp} \end{pmatrix}_{S+1} \tag{D.3}$$

So the mean of unconditional forecasts can be written as follows.

$$\begin{pmatrix} \hat{i}^{uc} \\ \hat{hp}^{uc} \end{pmatrix}_{S+1} = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}\begin{pmatrix} i \\ hp \end{pmatrix}_{T}$$

where *uc* denotes "unconditional forecast". Now impose following restriction on $e^{i}_{S+1} = b_{11}(i^{scenario}_{T+1} - \hat{i}^{uc}_{T+1})$ where the scenario could be "actual realization" or "simulated one" based on Taylor rule.

Equation (D.3) can be rewritten as follows.

$$\begin{pmatrix} i \\ hp \end{pmatrix}_{S+1} = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \begin{pmatrix} i \\ hp \end{pmatrix}_{S} + \begin{pmatrix} b_{11}^{-1} & 0 \\ -b_{21}/b_{11}b_{22} & b_{22}^{-1} \end{pmatrix} \begin{pmatrix} b_{11}(i^{scenario} - \hat{i}^{uc}) \\ e^{hp} \end{pmatrix}_{S+1} \tag{D.4}$$

After rewriting equation by equation for system (D.4), we can decompose each equation into unconditional forecast (=base projection) and the shocks.

$$\begin{aligned} i_{S+1} &= \overbrace{a_{11}i_S + a_{12}hp_S}^{\boxed{\text{Unconditional forecast}}} + \overbrace{i^{scenario}_{S+1} - \hat{i}^{uc}_{S+1}}^{\boxed{\text{shock}}} \\ &= a_{11}i_S + a_{12}hp_S + i^{scenario}_{S+1} - (a_{11}i_S + a_{12}hp_S) \\ &= i^{scenario}_{S+1} \end{aligned}$$

$$hp_{S+1} = \underbrace{a_{21}i_S + a_{22}hp_S}_{\boxed{\text{Unconditional forecast}}} + \underbrace{(-b_{21}/b_{22})(i^{scenario}_{S+1} - \hat{i}^{uc}_{S+1}) + b_{22}^{-1}e^{hp}_{S+1}}_{\boxed{\text{shock}}}$$

So the mean of conditional forecasts can be written as:

$$\begin{aligned} \hat{i}^{c}_{S+1} &= i^{scenario}_{S+1} \\ \hat{hp}^{c}_{S+1} &= a_{21}i_S + a_{22}hp_S + (-b_{21}/b_{22})(i^{scenario}_{S+1} - \hat{i}^{uc}_{S+1}) \end{aligned}$$

where *c* denotes "conditional forecast". For the two step-ahead conditional forecasts, these one step-ahead conditional forecasts are used to produce $\hat{i}^{uc}_{S+2}$ and $\hat{hp}^{uc}_{S+2}$ as follows.

$$\begin{pmatrix} \hat{i}^{uc} \\ \hat{hp}^{uc} \end{pmatrix}_{S+2} = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \begin{pmatrix} \hat{i}^{c} \\ \hat{hp}^{c} \end{pmatrix}_{S+1}$$

So in the multi step-ahead forecasts the dynamic coefficients also matter as well as the shocks when accounting the differences of conditional realizations among each assumed path of endogenous variables.

We can also obtain same results when approaching through conditional distribution. I keep using simplified version of bivariate VAR(1) with one step-ahead forecast case. Once deriving associated conditional distribution, we can verify that the mean of the structural shock *i* (restricted one) is reduced back to $e^{i}_{S+1} = b_{11}(i^{scenario}_{S+1} - \hat{i}^{uc}_{S+1})$ which is used in equation (D.4). As shown in equation (D.3), one step-ahead (*S*+*1*) forecasts are as follows.

$$\begin{pmatrix} i \\ hp \end{pmatrix}_{S+1} = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \begin{pmatrix} i \\ hp \end{pmatrix}_{S} + \begin{pmatrix} b_{11}^{-1} & 0 \\ -b_{21}/b_{11}b_{22} & b_{22}^{-1} \end{pmatrix} \begin{pmatrix} e^{i} \\ e^{hp} \end{pmatrix}_{S+1}$$

Above equation can be rewritten using condensed (or companion) form.

$$y_{S+1} = Ay_S + B^{-1}e_{S+1} \tag{D.5}$$

Now we pick e^{i}_{S+1} such that $\widetilde{B}^{-1}e_{S+1} = r_{S+1}$ where $r_{S+1} = i^{scenario}_{S+1} - \hat{i}^{uc}_{S+1}$. This is corresponding to the equation (10) in Waggoner and Zha (1999).

$$\widetilde{B}^{-1}e_{S+1} = r_{S+1} \Rightarrow \begin{pmatrix} b_{11}^{-1} & 0 \end{pmatrix} \begin{pmatrix} e^{i} \\ e^{hp} \end{pmatrix}_{S+1} = i^{scenario}_{S+1} - \hat{i}^{uc}_{S+1}, \text{ therefore, } e^{i}_{S+1} = b_{11}(i^{scenario}_{S+1} - \hat{i}^{uc}_{S+1}) \tag{D.6}$$

As discussed in Waggoner and Zha (1999), the joint distribution of e^{i}_{S+1} and $\widetilde{B}^{-1}e_{S+1}$ is multivariate normal. Hereafter matrix notation is used for the consistent notations with previous literatures. That is, e indicates not only multivariate but also multi step-ahead forecasts while e^i_{S+1} indicates single variable i and one step-ahead case.

$$Ee = 0,\ E\tilde{B}^{-1}e = 0,$$
$$\mathrm{var}(e) = I,\ \mathrm{var}(\tilde{B}^{-1}e) = \tilde{B}^{-1}\,\mathrm{var}(e)(\tilde{B}^{-1})' = \tilde{B}^{-1}(\tilde{B}^{-1})'$$
$$\mathrm{cov}(e, \tilde{B}^{-1}e) = E\{(e - Ee)(\tilde{B}^{-1}e - E\tilde{B}^{-1}e)'\} = E\{ee'(\tilde{B}^{-1})'\} = (\tilde{B}^{-1})'$$

Therefore,

$$\begin{pmatrix} e \\ \tilde{B}^{-1}e \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} I & (\tilde{B}^{-1})' \\ \tilde{B}^{-1} & \tilde{B}^{-1}(\tilde{B}^{-1})' \end{pmatrix} \right) \tag{D.7}$$

After applying theorem with respect to conditional normal distribution (Greene (2003, pp871-872)), I reach final conditional distribution as shown in equation (D.8). This is corresponding to the equation (12) in Waggoner and Zha (1999).

$$e\Big|_{\tilde{B}^{-1}e=r} \sim N\left((\tilde{B}^{-1})'(\tilde{B}^{-1}(\tilde{B}^{-1})')^{-1}r,\ I - (\tilde{B}^{-1})'(\tilde{B}^{-1}(\tilde{B}^{-1})')^{-1}\tilde{B}^{-1} \right) \tag{D.8}$$

We can verify that the mean of shock i (restricted) is reduced back to equation (D.6) with variance zero while the shock hp (unrestricted) has usual form of structural shock which is mean zero and variance one.

(Mean)

$$(\tilde{B}^{-1})'(\tilde{B}^{-1}(\tilde{B}^{-1})')^{-1}r = \begin{pmatrix} b_{11}^{-1} \\ 0 \end{pmatrix} \left\{ \begin{pmatrix} b_{11}^{-1} & 0 \end{pmatrix} \begin{pmatrix} b_{11}^{-1} \\ 0 \end{pmatrix} \right\}^{-1} \left(i_{S+1}^{scenario} - \hat{i}_{S+1}^{uc} \right) = \begin{pmatrix} b_{11}(i_{S+1}^{scenario} - \hat{i}_{S+1}^{uc}) \\ 0 \end{pmatrix}$$

(Covariance)

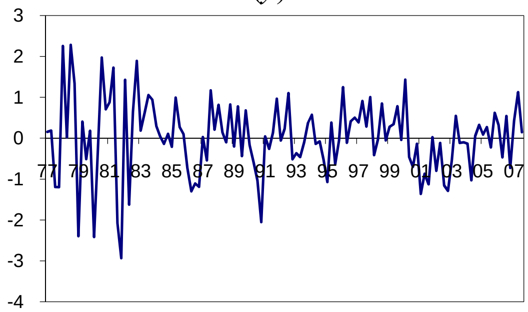
$$\begin{aligned} I - (\tilde{B}^{-1})'(\tilde{B}^{-1}(\tilde{B}^{-1})')^{-1}\tilde{B}^{-1} &= \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} - \begin{pmatrix} b_{11}^{-1} \\ 0 \end{pmatrix} \left\{ \begin{pmatrix} b_{11}^{-1} & 0 \end{pmatrix} \begin{pmatrix} b_{11}^{-1} \\ 0 \end{pmatrix} \right\}^{-1} \begin{pmatrix} b_{11}^{-1} & 0 \end{pmatrix} \\ &= \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} - \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix} = \begin{pmatrix} 0 & 0 \\ 0 & 1 \end{pmatrix} \end{aligned}$$

APPENDIX E

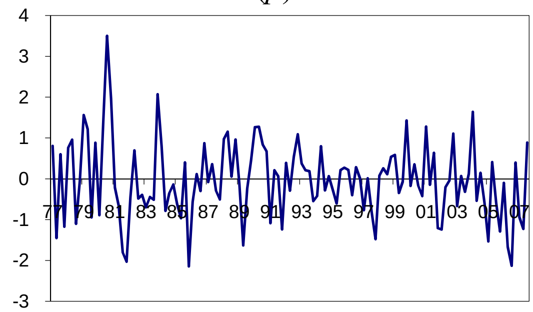
ESTIMATED STRUCTURAL SHOCKS

(Choleski)

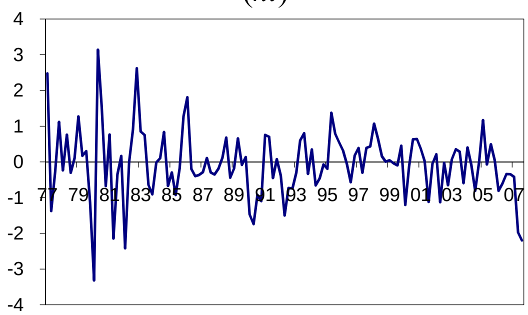
(y)



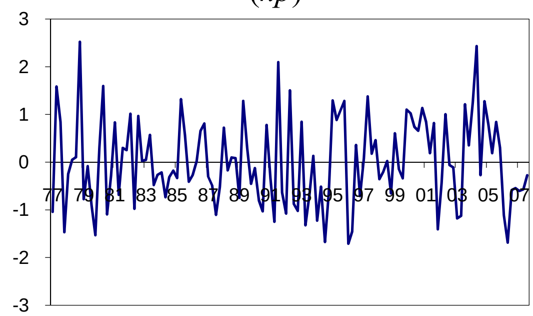
(p)



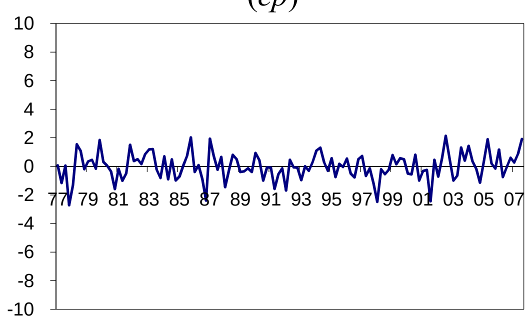
(hi)



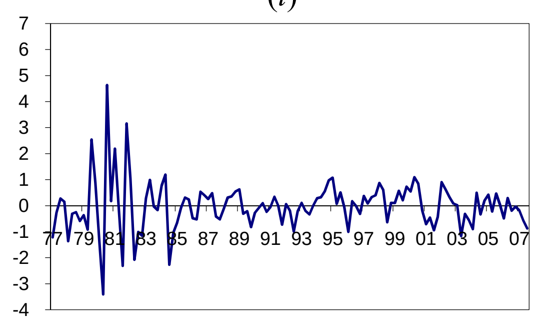
(hp)



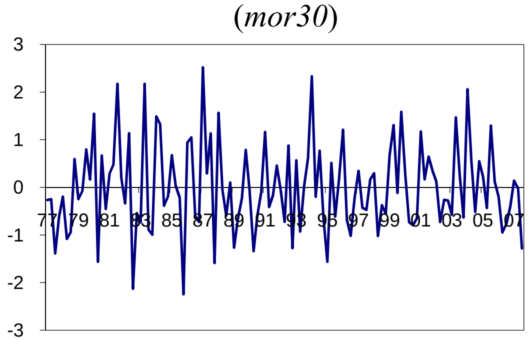
(cp)



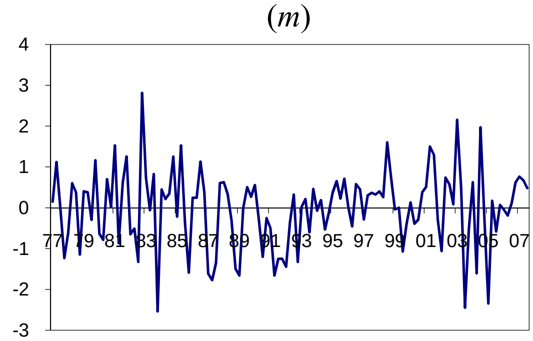
(i)



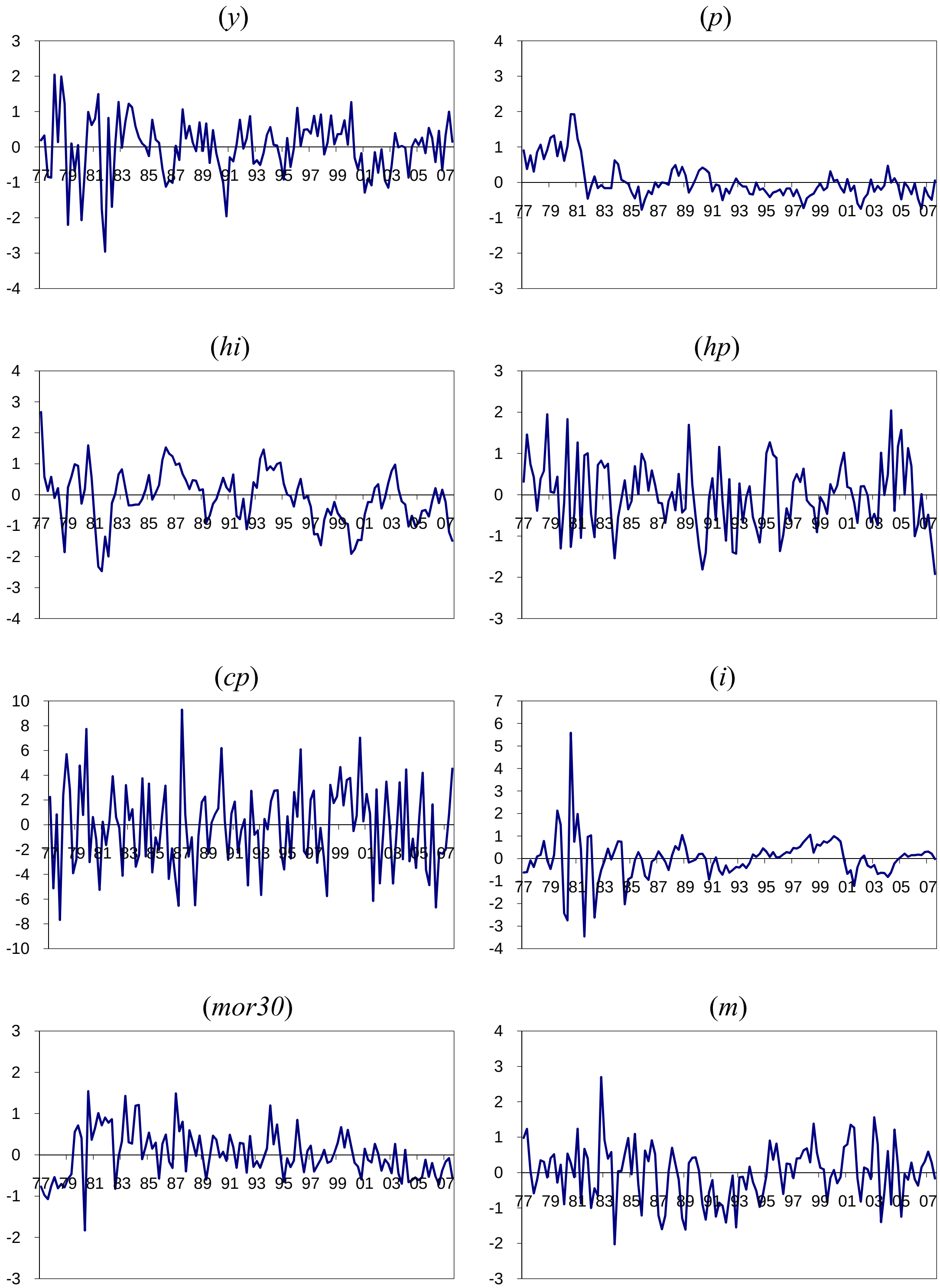
($mor30$)



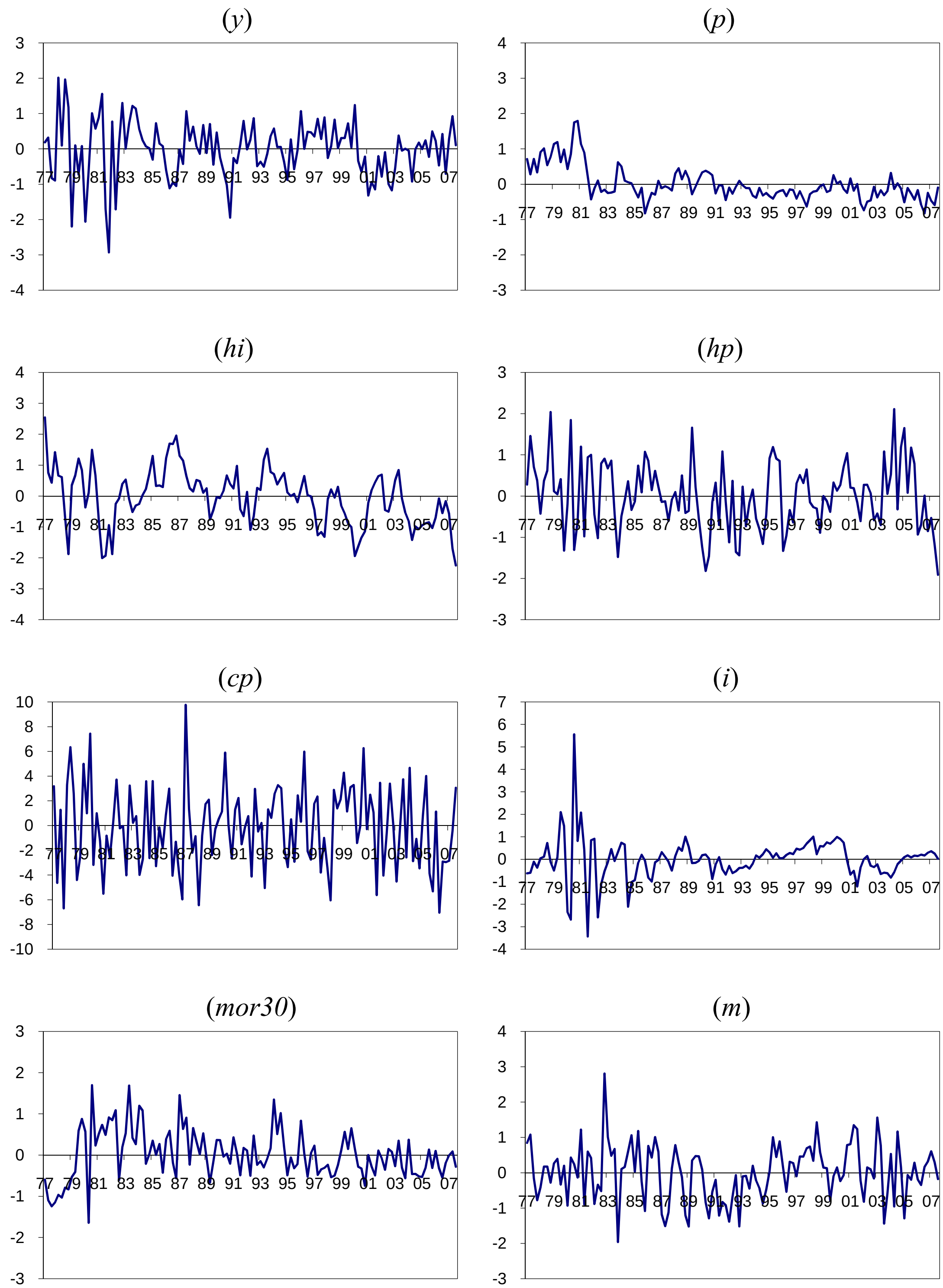
(m)



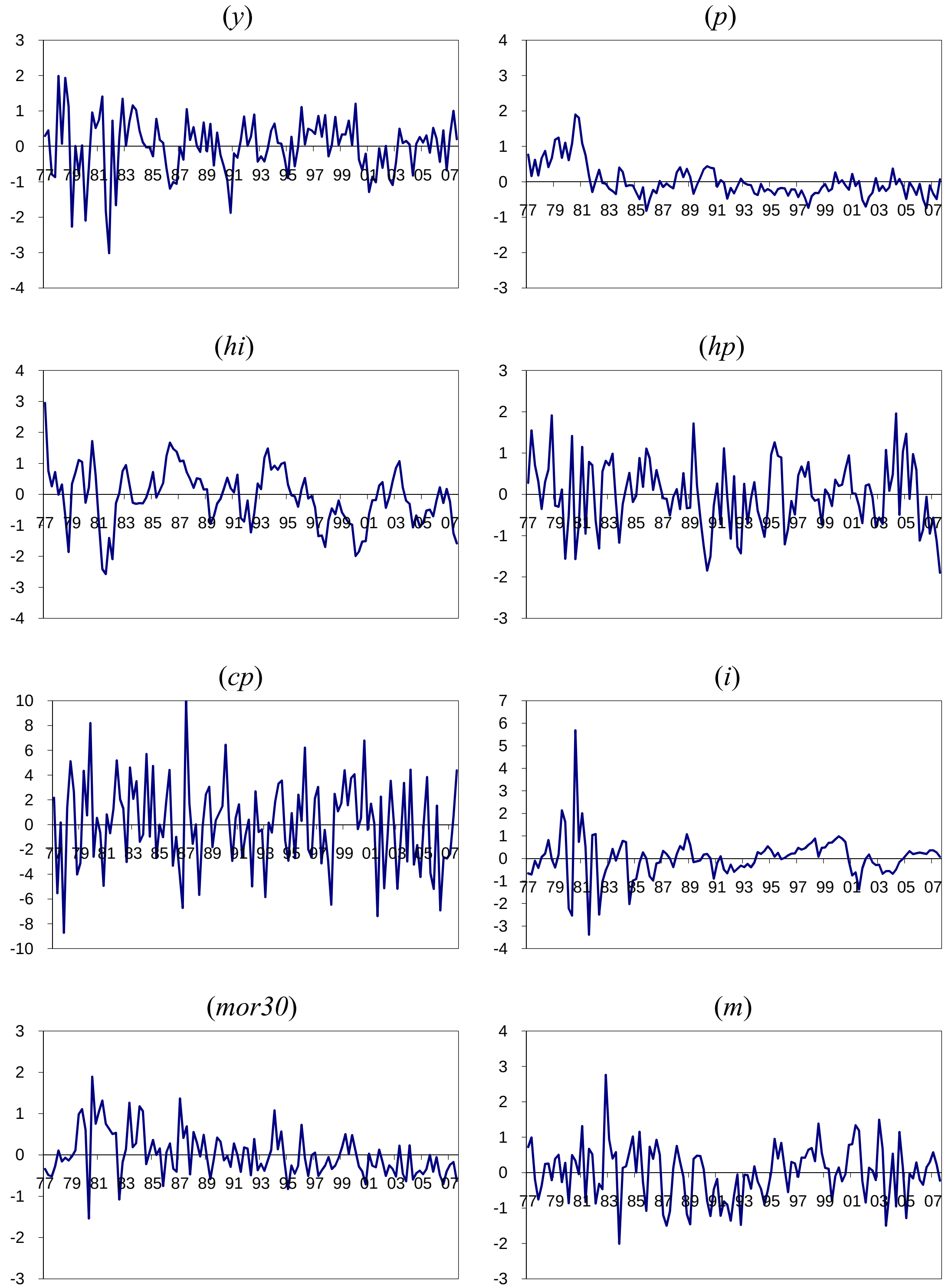
(GL+)



(SZ+)

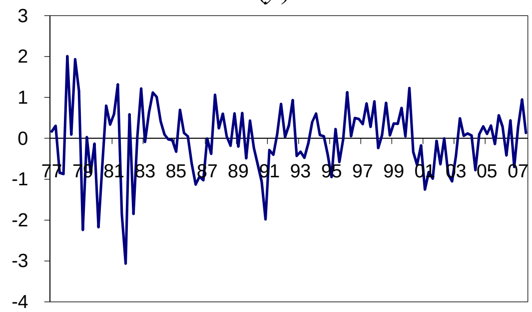


(PC)

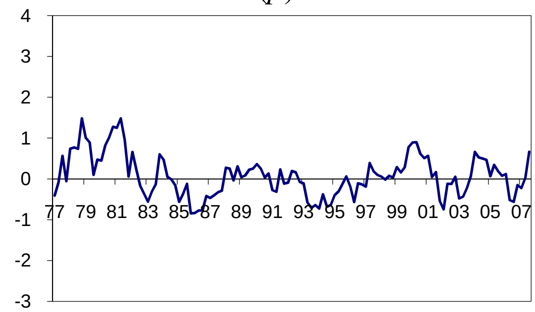


(GES)

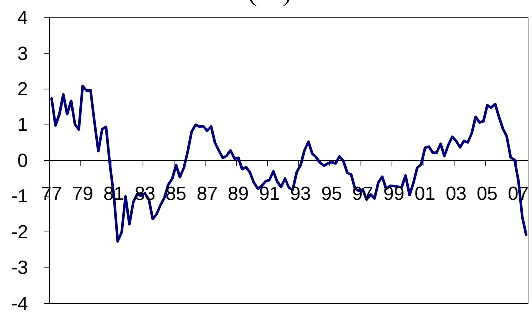
(*y*)



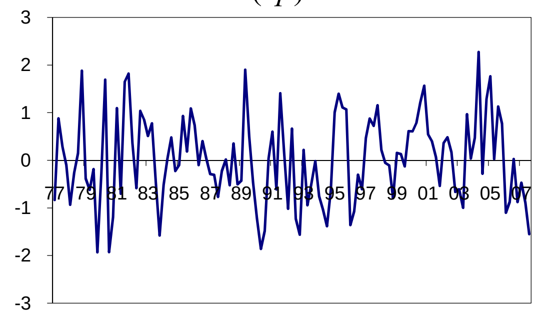
(*p*)



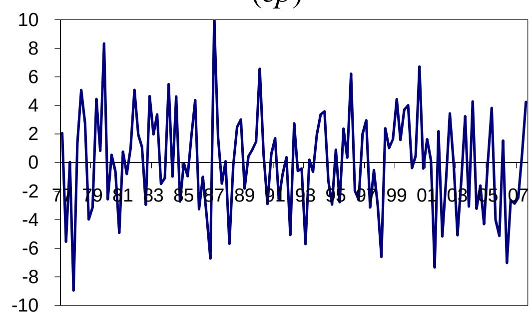
(*hi*)



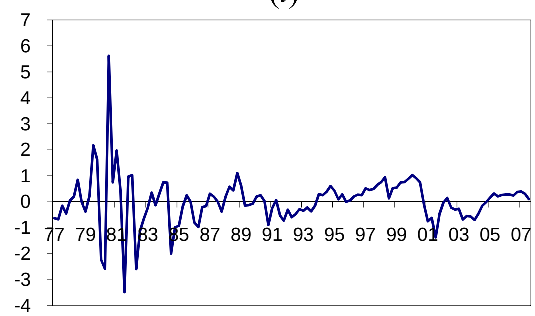
(*hp*)



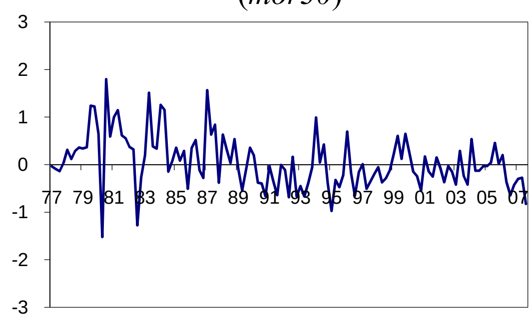
(*cp*)



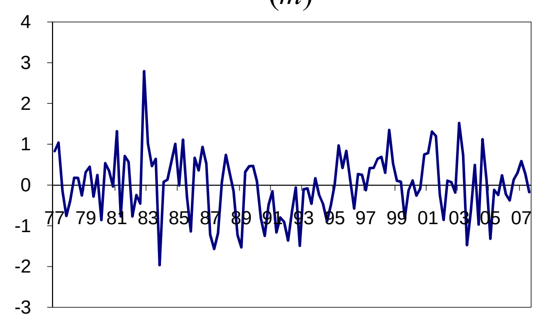
(*i*)



(*mor30*)



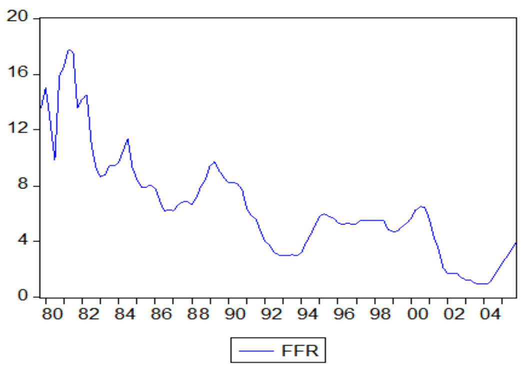
(*m*)



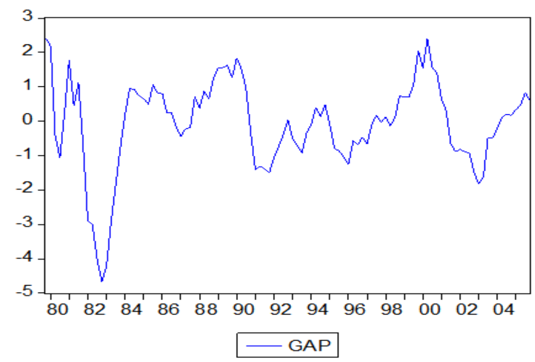
APPENDIX F

PLOTS OF EACH VARIABLE IN CHAPTER IV

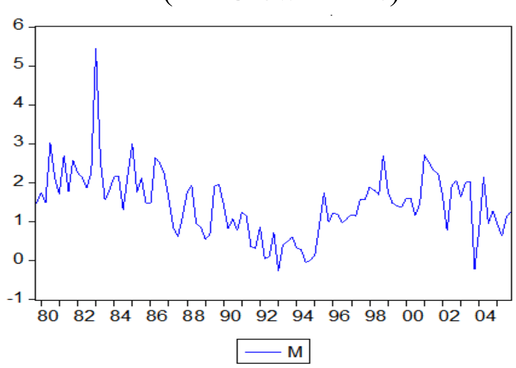
(Federal Funds Rate)



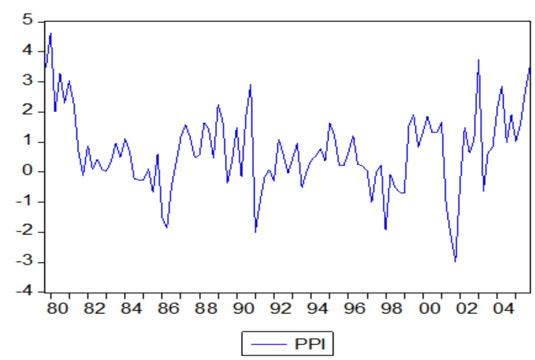
(Real GDP's % Deviation from HP trend)



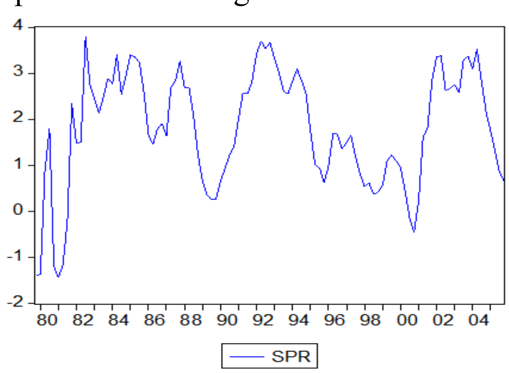
(M2 Growth Rate)



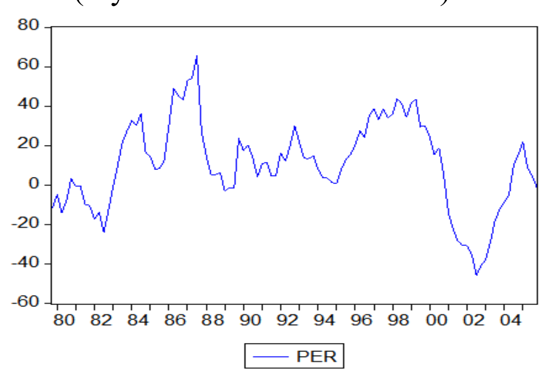
(PPI Growth Rate)



(Spread betIen Long and Short-term Bond)



(2-year Growth Rate of PER)



APPENDIX G

TEST RESULTS OF CHOOSING IVS

(General Model)

$$E(e_t Z_t) = E\{[R_t - \rho D_1 R_{t-1} - (1-\rho D_1)\{D_1\theta + (\alpha_0 + \alpha_1\delta_t + \alpha_2\delta_t^2)D_1\pi_{t+k} + \beta D_1 y_{t+k}$$
$$+ (\gamma_0 + \gamma_1\delta_t + \gamma_2\delta_t^2)D_1 s_t\} - \rho D_2 R_{t-1} - (1-\rho D_2)\{D_2\theta + (\alpha_0 + \alpha_1\delta_t + \alpha_2\delta_t^2)D_2\pi_{t+k}$$
$$+ \beta D_2 y_{t+k} + (\gamma_0 + \gamma_1\delta_t + \gamma_2\delta_t^2)D_2 s_t]\, Z_t\} = 0$$

where $D_1 = \begin{cases} 1\ if\ t \le q1\,1991 \\ 0\ if\ t > q2\,1991 \end{cases}$ $D_2 = \begin{cases} 0\ if\ t \le q1\,1991 \\ 1\ if\ t > q1\,1991 \end{cases}$

GMM-BIC Criteria

	J-statistic	*# of over-id.*	*ln(n), n=101*	*GMM-BIC*
3lags	0.10	3	4.62	-13.74
4lags	0.31	8	4.62	-36.61
5lags	1.85	13	4.62	-58.14
6lags	3.28	19	4.62	-84.41
7lags	5.59	25	4.62	-109.79
8lags	11.76	31	4.62	-131.31
9lags	14.15	37	4.62	-156.61
10lags	22.11	43	4.62	-176.34
11lags	25.37	49	4.62	-200.78
12lags	26.85	55	4.62	-226.98
13lags	37.39	61	4.62	-244.13
14lags	**36.12**	**67**	**4.62**	**-273.09**
15lags	155.40	73	4.62	-181.50
16lags	3433.59	79	4.62	3068.99

GMM-HQIC Criteria (General Model)

	J-statistic	*# of over-id.*	*ln(ln(n)), n=101*	*(Q=2.01)*	*(Q=3)*	*(Q=4)*	*(Q=5)*
3lags	0.10	3	0.30	-1.72	-2.61	-3.52	-4.43
4lags	0.31	8	0.30	-4.55	-6.94	-9.36	-11.77
5lags	1.85	13	0.30	-6.04	-9.92	-13.85	-17.78
6lags	3.28	19	0.30	-8.25	-13.93	-19.67	-25.41
7lags	5.59	25	0.30	**-9.58**	-17.06	-24.61	-32.16
8lags	11.76	31	0.30	-7.06	-16.33	-25.69	-35.05
9lags	14.15	37	0.30	-8.31	-19.37	-30.54	-41.72
10lags	22.11	43	0.30	-3.99	-16.85	-29.83	-42.82
11lags	25.37	49	0.30	-4.38	-19.02	-33.82	-48.62
12lags	26.85	55	0.30	-6.54	-22.98	-39.59	-56.19
13lags	37.39	61	0.30	0.37	-17.87	-36.29	-54.71
14lags	**36.12**	**67**	**0.30**	-4.54	**-24.57**	**-44.80**	**-65.04**
15lags	155.40	73	0.30	111.10	89.27	67.23	45.19
16lags	3433.59	79	0.30	3385.64	3362.02	3338.17	3314.31

(Linear Restriction on Stock price gap coefficient)

$$E(e_t Z_t) = E\{[R_t - \rho D_1 R_{t-1} - (1-\rho D_1)\{D_1\theta + (\alpha_0 + \alpha_1\delta_t + \alpha_2\delta_t^2) D_1\pi_{t+k} + \beta D_1 y_{t+k}$$
$$+ \gamma_0 D_1 s_t\} - \rho D_2 R_{t-1} - (1-\rho D_2)\{D_2\theta + (\alpha_0 + \alpha_1\delta_t + \alpha_2\delta_t^2) D_2\pi_{t+k} + \beta D_2 y_{t+k}$$
$$+ \gamma_0 D_2 s_t]\, Z_t\} = 0$$
$$where\ D_1 = \begin{cases} 1\ if\ t \le q1\,1991 \\ 0\ if\ t > q2\,1991 \end{cases} \quad D_2 = \begin{cases} 0\ if\ t \le q1\,1991 \\ 1\ if\ t > q1\,1991 \end{cases}$$

GMM-BIC Criteria

	J-statistic	*# of over-id.*	*ln(n), n=101*	*GMM-BIC*
3lags	0.92	7	4.62	-31.39
4lags	2.53	12	4.62	-52.85
5lags	5.31	17	4.62	-73.15
6lags	6.28	23	4.62	-99.87
7lags	8.65	29	4.62	-125.19
8lags	13.07	35	4.62	-148.46
9lags	16.22	41	4.62	-173.00
10lags	23.10	47	4.62	-193.81
11lags	26.04	53	4.62	-218.56
12lags	28.55	59	4.62	-243.74
13lags	37.13	65	4.62	-262.86
14lags	**56.38**	**71**	**4.62**	**-271.30**
15lags	87.68	77	4.62	-267.69
16lags	1089.64	83	4.62	706.59

GMM-HQIC Criteria

	J-statistic	*# of over-id.*	*ln(ln(n)), n=101*	*(Q=2.01)*	*(Q=3)*	*(Q=4)*	*(Q=5)*
3lags	0.92	7	0.30	-3.33	-5.43	-7.54	-9.65
4lags	2.53	12	0.30	-4.76	-8.34	-11.97	-15.59
5lags	5.31	17	0.30	-5.01	-10.09	-15.23	-20.36
6lags	6.28	23	0.30	-7.68	-14.56	-21.50	-28.45
7lags	8.65	29	0.30	**-8.95**	-17.62	-26.38	-35.14
8lags	13.07	35	0.30	-8.18	-18.64	-29.21	-39.78
9lags	16.22	41	0.30	-8.67	-20.92	-33.30	-45.69
10lags	23.10	47	0.30	-5.43	-19.48	-33.67	-47.86
11lags	26.04	53	0.30	-6.13	-21.97	-37.98	-53.98
12lags	**28.55**	59	**0.30**	-7.26	**-24.90**	**-42.71**	-60.53
13lags	**37.13**	**65**	**0.30**	-2.33	-21.76	-41.39	**-61.01**
14lags	56.38	71	0.30	13.28	-7.94	-29.38	-50.82

APPENDIX H

TEST RESULTS OF STRUCTURAL CHANGE FOR 10, 11, 13, AND 14 LAGS IVS

(Tests for Stability of Coefficients across Sub-periods: *Case of 10 lags IV*)

(i) General Model: Dummy variables for all coefficients. Over-identification: 61 - 18 = 43

$$E(e_t Z_t) = E\{[R_t - \rho D_1 R_{t-1} - (1-\rho D_1)\{D_1\theta + (\alpha_0 + \alpha_1\delta_t + \alpha_2\delta_t^2)D_1\pi_{t+k} + \beta D_1 y_{t+k} + (\gamma_0 + \gamma_1\delta_t + \gamma_2\delta_t^2)D_1 s_t\} - \rho D_2 R_{t-1} - (1-\rho D_2)\{D_2\theta + (\alpha_0 + \alpha_1\delta_t + \alpha_2\delta_t^2)D_2\pi_{t+k} + \beta D_2 y_{t+k} + (\gamma_0 + \gamma_1\delta_t + \gamma_2\delta_t^2)D_2 s_t]\, Z_t\} = 0$$

where $(D_1)' = [1\,1\cdots, 0\,0\cdots 0]$ $\quad (D_2)' = [0\,0\cdots 0, 1\,1\cdots 1]$

	α_0	α_1	α_2	β	ρ	θ	γ_0	γ_1	γ_2	*J-statistic*
1979:4 – 1991:1	1.079 (0.152)	0.218 (0.028)	-0.003 (0.007)	0.015 (0.168)	0.470 (0.070)	5.667 (0.677)	-0.032 (0.019)	0.004 (0.009)	-0.001 (0.005)	22.106 [0.9966]
1991:2 – 2005:4	4.668 (6.895)	0.423 (0.356)	-0.663 (0.831)	-0.154 (0.906)	0.833 (0.179)	-5.527 (14.35)	0.104 (0.106)	-0.004 (0.046)	-0.005 (0.035)	

Nonlinearity Test

Null: $\alpha_1^h = \alpha_2^h = \alpha_1^l = \alpha_2^l = \gamma_1^h = \gamma_2^h = \gamma_1^l = \gamma_2^l = 0$: p-value = 0.0000

Null: $\alpha_1^h = \alpha_1^l = \alpha_2^h = \alpha_2^l = 0$: p-value = 0.0000

Null: $\gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.9910

Wald Test for Stability of Coefficients

Null: $\alpha_0^h = \alpha_0^l, \alpha_1^h = \alpha_1^l, \alpha_2^h = \alpha_2^l, \beta^h = \beta^l, \rho^h = \rho^l, \theta^h = \theta^l, \gamma_0^h = \gamma_0^l, \gamma_1^h = \gamma_1^l, \gamma_2^h = \gamma_2^l$: p-value = 0.0000

Null: $\alpha_0^h = \alpha_0^l, \alpha_1^h = \alpha_1^l, \alpha_2^h = \alpha_2^l, \gamma_0^h = \gamma_0^l, \gamma_1^h = \gamma_1^l, \gamma_2^h = \gamma_2^l \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l$: p-value = 0.0004

Null: $\alpha_0^h = \alpha_0^l, \alpha_1^h = \alpha_1^l, \alpha_2^h = \alpha_2^l \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l$: p-value = 0.7306

Null: $\gamma_0^h = \gamma_0^l, \gamma_1^h = \gamma_1^l, \gamma_2^h = \gamma_2^l \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l$: p-value = 0.2362

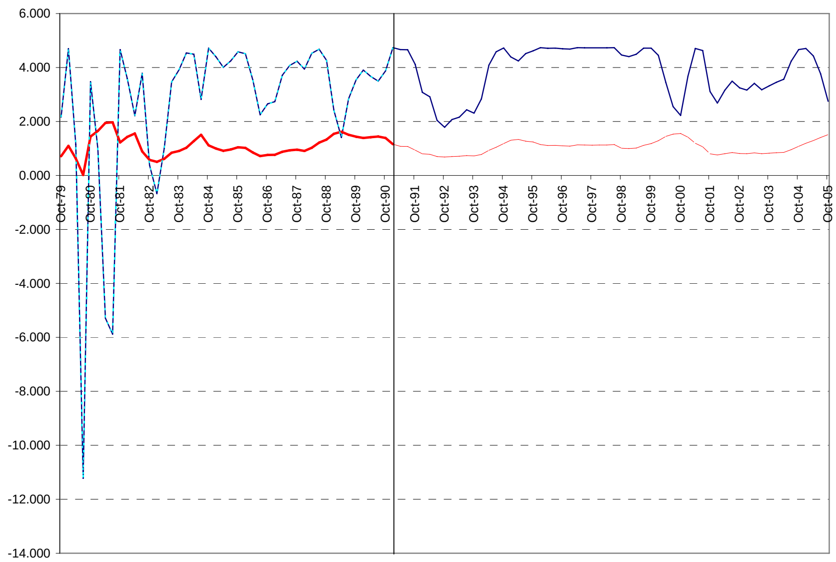


Fig. H.1 Inflation coefficient movement: General model (10 lags IV)

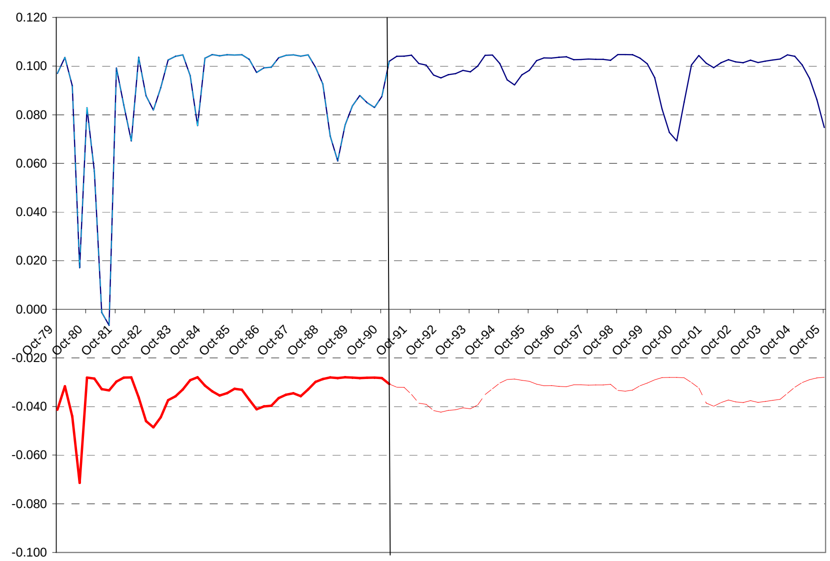


Fig. H.2 Stock variable coefficient movement: General model(10 lags IV)

(ii) Linear Restriction on Stock Variable Coefficient. Over-identification: 61-14 = 47

$$E(e_t Z_t) = E\{[R_t - \rho D_1 R_{t-1} - (1-\rho D_1)\{D_1\theta + (\alpha_0 + \alpha_1\delta_t + \alpha_2\delta_t^2)D_1\pi_{t+k} + \beta D_1 y_{t+k}$$
$$+\gamma_0 D_1 s_t\} - \rho D_2 R_{t-1} - (1-\rho D_2)\{D_2\theta + (\alpha_0 + \alpha_1\delta_t + \alpha_2\delta_t^2)D_2\pi_{t+k} + \beta D_2 y_{t+k}$$
$$+\gamma_0 D_2 s_t] Z_t\} = 0$$
where $(D_1)' = [1\,1\cdots, 0\,0\cdots 0]$ $(D_2)' = [0\,0\cdots 0, 1\,1\cdots 1]$

	α_0	α_1	α_2	β	ρ	θ	γ_0	*J-statistic*
1979:4 – 1991:1	1.090 (0.129)	0.219 (0.028)	-0.003 (0.004)	0.035 (0.147)	0.479 (0.067)	5.630 (0.566)	-0.035 (0.008)	23.1 [0.9987]
1991:2 – 2005:4	4.198 (4.930)	0.436 (0.290)	-0.615 (0.613)	-0.169 (0.727)	0.818 (0.154)	-4.506 (9.924)	0.094 (0.052)	

Nonlinearity Test

Null: $\alpha_1^h = \alpha_2^h = \alpha_1^l = \alpha_2^l = 0 \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l, \gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.0000

Null: $\alpha_1^h = \alpha_2^h = 0 \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l, \gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.0000

Null: $\alpha_1^l = \alpha_2^l = 0 \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l, \gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.2252

Wald Test for Stability of Coefficients

Null: $\alpha_0^h = \alpha_0^l, \alpha_1^h = \alpha_1^l, \alpha_2^h = \alpha_2^l, \beta^h = \beta^l, \rho^h = \rho^l, \theta^h = \theta^l, \gamma_0^h = \gamma_0^l \mid \gamma_1^h = \gamma_2^h = \gamma_1^l = \gamma_2^l = 0$: p-value = 0.0000

Null: $\alpha_0^h = \alpha_0^l, \alpha_1^h = \alpha_1^l, \alpha_2^h = \alpha_2^l, \gamma_0^h = \gamma_0^l \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l, \gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.0000

Null: $\alpha_0^h = \alpha_0^l, \alpha_1^h = \alpha_1^l, \alpha_2^h = \alpha_2^l \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l, \gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.1883

Null: $\gamma_0^h = \gamma_0^l \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l, \gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.0176

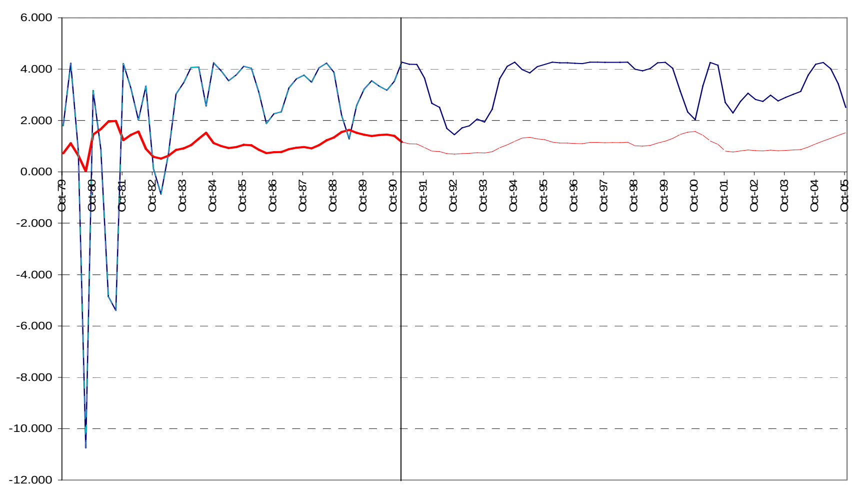


Fig.H.3 Inflation coefficient movement: Linear restriction on stock variable coefficient (10 lags IV)

(Tests for Stability of Coefficients across Sub-periods: *Case of 11 lags IV*)

(i) General Model: Dummy variables for all coefficients. Over-identification: 67 - 18 = 49

$$\begin{aligned} E(e_t Z_t) = E\{[R_t - \rho D_1 R_{t-1} - (1-\rho D_1)\{D_1\theta + (\alpha_0 + \alpha_1\delta_t + \alpha_2\delta_t^2)D_1\pi_{t+k} + \beta D_1 y_{t+k} \\ + (\gamma_0 + \gamma_1\delta_t + \gamma_2\delta_t^2)D_1 s_t\} - \rho D_2 R_{t-1} - (1-\rho D_2)\{D_2\theta + (\alpha_0 + \alpha_1\delta_t + \alpha_2\delta_t^2)D_2\pi_{t+k} \\ + \beta D_2 y_{t+k} + (\gamma_0 + \gamma_1\delta_t + \gamma_2\delta_t^2)D_2 s_t]\, Z_t\} = 0 \end{aligned}$$

where $(D_1)' = [1\,1\cdots, 0\,0\cdots 0] \quad (D_2)' = [0\,0\cdots 0, 1\,1\cdots 1]$

	α_0	α_1	α_2	β	ρ	θ	γ_0	γ_1	γ_2	*J-statistic*
1979:4 – 1991:1	1.203 (0.142)	0.243 (0.027)	-0.002 (0.005)	0.078 (0.162)	0.530 (0.053)	4.887 (0.645)	-0.023 (0.011)	0.002 (0.005)	0.0001 (0.003)	25.365 [0.9979]
1991:2 – 2005:4	5.427 (6.206)	0.453 (0.294)	-0.755 (0.750)	-0.674 (0.769)	0.852 (0.141)	-7.183 (13.21)	0.119 (0.107)	0.035 (0.056)	0.022 (0.034)	

Nonlinearity Test

Null: $\alpha_1^h = \alpha_2^h = \alpha_1^l = \alpha_2^l = \gamma_1^h = \gamma_2^h = \gamma_1^l = \gamma_2^l = 0$: p-value = 0.0000

Null: $\alpha_1^h = \alpha_1^l = \alpha_2^h = \alpha_2^l = 0$: p-value = 0.0000

Null: $\gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.9608

Wald Test for Stability of Coefficients

Null: $\alpha_0^h = \alpha_0^l, \alpha_1^h = \alpha_1^l, \alpha_2^h = \alpha_2^l, \beta^h = \beta^l, \rho^h = \rho^l, \theta^h = \theta^l, \gamma_0^h = \gamma_0^l, \gamma_1^h = \gamma_1^l, \gamma_2^h = \gamma_2^l$: p-value = 0.0000

Null: $\alpha_0^h = \alpha_0^l, \alpha_1^h = \alpha_1^l, \alpha_2^h = \alpha_2^l, \gamma_0^h = \gamma_0^l, \gamma_1^h = \gamma_1^l, \gamma_2^h = \gamma_2^l \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l$: p-value = 0.0011

Null: $\alpha_0^h = \alpha_0^l, \alpha_1^h = \alpha_1^l, \alpha_2^h = \alpha_2^l \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l$: p-value = 0.5292

Null: $\gamma_0^h = \gamma_0^l, \gamma_1^h = \gamma_1^l, \gamma_2^h = \gamma_2^l \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l$: p-value = 0.1655

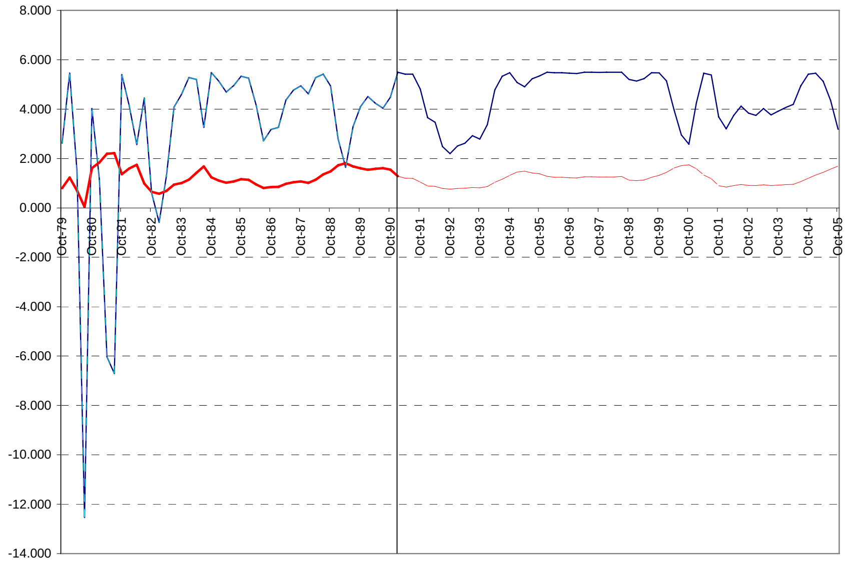


Fig. H.4. Inflation coefficient movement: General model (11 lags IV)

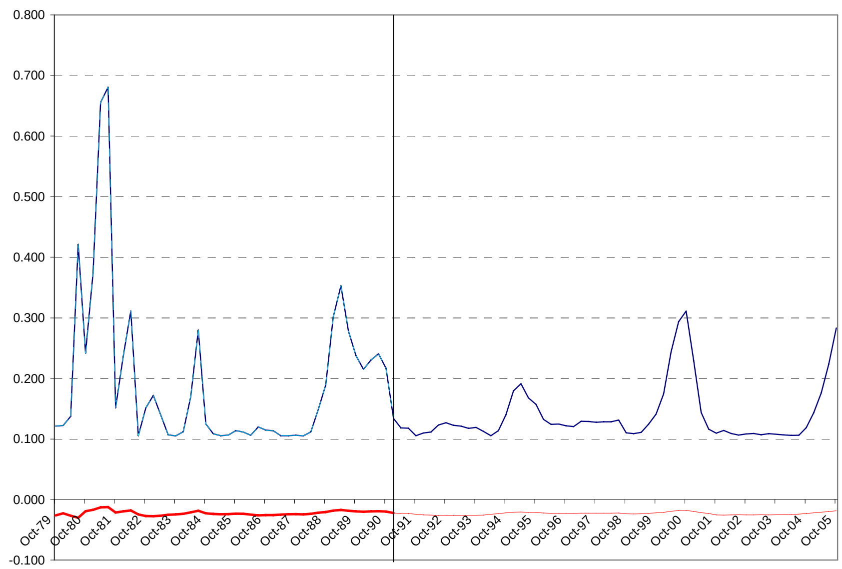


Fig. H.5. Stock variable coefficient movement: General model (11 lags IV)

(ii) Linear Restriction on Stock Variable Coefficient. Over-identification: 67-14 = 53

$$E(e_t Z_t) = E\{[R_t - \rho D_1 R_{t-1} - (1-\rho D_1)\{D_1\theta + (\alpha_0 + \alpha_1\delta_t + \alpha_2\delta_t^2)D_1\pi_{t+k} + \beta D_1 y_{t+k} + \gamma_0 D_1 s_t\} - \rho D_2 R_{t-1} - (1-\rho D_2)\{D_2\theta + (\alpha_0 + \alpha_1\delta_t + \alpha_2\delta_t^2)D_2\pi_{t+k} + \beta D_2 y_{t+k} + \gamma_0 D_2 s_t]\, Z_t\} = 0$$

where $(D_1)' = [1\,1\cdots,0\,0\cdots0] \quad (D_2)' = [0\,0\cdots0,1\,1\cdots1]$

	α_0	α_1	α_2	β	ρ	θ	γ_0	*J-statistic*
1979:4 – 1991:1	1.260 (0.118)	0.243 (0.026)	-0.003 (0.003)	0.114 (0.137)	0.539 (0.052)	4.658 (0.577)	-0.023 (0.007)	26.040 [0.9993]
1991:2 – 2005:4	3.454 (2.394)	0.489 (0.157)	-0.444 (0.300)	-0.525 (0.448)	0.800 (0.096)	-3.110 (4.859)	0.094 (0.033)	

Nonlinearity Test

Null: $\alpha_1^h = \alpha_2^h = \alpha_1^l = \alpha_2^l = 0 \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l, \gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.0000

Null: $\alpha_1^h = \alpha_2^h = 0 \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l, \gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.0000

Null: $\alpha_1^l = \alpha_2^l = 0 \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l, \gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.0053

Wald Test for Stability of Coefficients

Null: $\alpha_0^h = \alpha_0^l, \alpha_1^h = \alpha_1^l, \alpha_2^h = \alpha_2^l, \beta^h = \beta^l, \rho^h = \rho^l, \theta^h = \theta^l, \gamma_0^h = \gamma_0^l \mid \gamma_1^h = \gamma_2^h = \gamma_1^l = \gamma_2^l = 0$: p-value = 0.0000

Null: $\alpha_0^h = \alpha_0^l, \alpha_1^h = \alpha_1^l, \alpha_2^h = \alpha_2^l, \gamma_0^h = \gamma_0^l \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l, \gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.0000

Null: $\alpha_0^h = \alpha_0^l, \alpha_1^h = \alpha_1^l, \alpha_2^h = \alpha_2^l \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l, \gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.0278

Null: $\gamma_0^h = \gamma_0^l \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l, \gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.0007

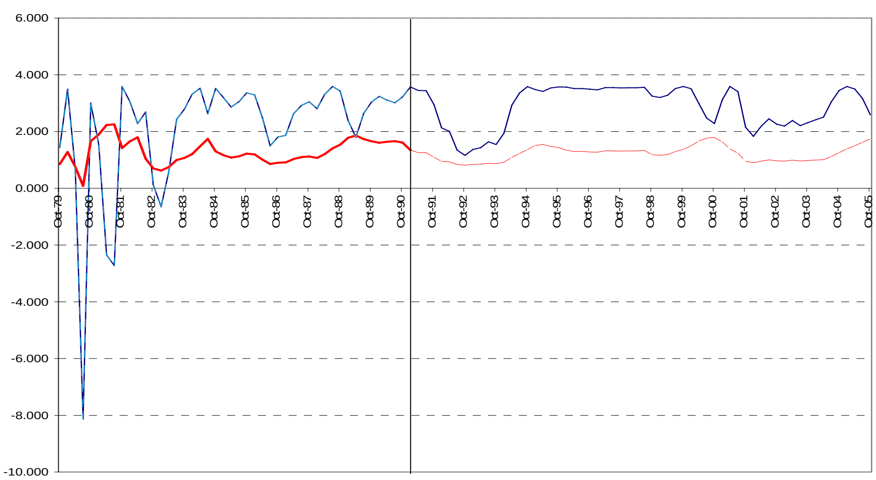


Fig. H.6. Inflation coefficient movement: Linear restriction on stock variable coefficient (11 lags IV)

(Tests for Stability of Coefficients across Sub-periods: *Case of 12 lags IV*)

Linear Restriction on Stock Variable Coefficient

$$E(e_t Z_t) = E\{[R_t - \rho D_1 R_{t-1} - (1-\rho D_1)\{D_1\theta + (\alpha_0 + \alpha_1\delta_t + \alpha_2\delta_t^2)D_1\pi_{t+k} + \beta D_1 y_{t+k} + \gamma_0 D_1 s_t\} - \rho D_2 R_{t-1} - (1-\rho D_2)\{D_2\theta + (\alpha_0 + \alpha_1\delta_t + \alpha_2\delta_t^2)D_2\pi_{t+k} + \beta D_2 y_{t+k} + \gamma_0 D_2 s_t]\, Z_t\} = 0$$

$$\text{where } D_1 = \begin{cases} 1 \text{ if } t \le q1\,1991 \\ 0 \text{ if } t > q2\,1991 \end{cases} \quad D_2 = \begin{cases} 0 \text{ if } t \le q1\,1991 \\ 1 \text{ if } t > q1\,1991 \end{cases}$$

	α_0	α_1	α_2	β	ρ	θ	γ_0	*J-statistic*
1979:4 – 1991:1	1.263 (0.068)	0.251 (0.020)	0.002 (0.002)	0.129 (0.108)	0.547 (0.035)	4.475 (0.336)	-0.017 (0.005)	28.55 [0.9997]
1991:2 – 2005:4	1.442 (0.879)	0.471 (0.079)	-0.228 (0.105)	-0.359 (0.260)	0.740 (0.066)	0.949 (1.786)	0.065 (0.012)	

Nonlinearity Test

Null: $\alpha_1^h = \alpha_2^h = \alpha_1^l = \alpha_2^l = 0 \mid \beta^h \ne \beta^l, \rho^h \ne \rho^l, \theta^h \ne \theta^l, \gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.0000

Null: $\alpha_1^h = \alpha_2^h = 0 \mid \beta^h \ne \beta^l, \rho^h \ne \rho^l, \theta^h \ne \theta^l, \gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.0000

Null: $\alpha_1^l = \alpha_2^l = 0 \mid \beta^h \ne \beta^l, \rho^h \ne \rho^l, \theta^h \ne \theta^l, \gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.0000

Wald Test for Stability of Coefficients

Null: $\alpha_0^h = \alpha_0^l, \alpha_1^h = \alpha_1^l, \alpha_2^h = \alpha_2^l, \beta^h = \beta^l, \rho^h = \rho^l, \theta^h = \theta^l, \gamma_0^h = \gamma_0^l \mid \gamma_1^h = \gamma_2^h = \gamma_1^l = \gamma_2^l = 0$:p-value = 0.0000

Null: $\alpha_0^h = \alpha_0^l, \alpha_1^h = \alpha_1^l, \alpha_2^h = \alpha_2^l, \gamma_0^h = \gamma_0^l \mid \beta^h \ne \beta^l, \rho^h \ne \rho^l, \theta^h \ne \theta^l, \gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.0000

Null: $\alpha_0^h = \alpha_0^l, \alpha_1^h = \alpha_1^l, \alpha_2^h = \alpha_2^l \mid \beta^h \ne \beta^l, \rho^h \ne \rho^l, \theta^h \ne \theta^l, \gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.0000

Null: $\gamma_0^h = \gamma_0^l \mid \beta^h \ne \beta^l, \rho^h \ne \rho^l, \theta^h \ne \theta^l, \gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.0000

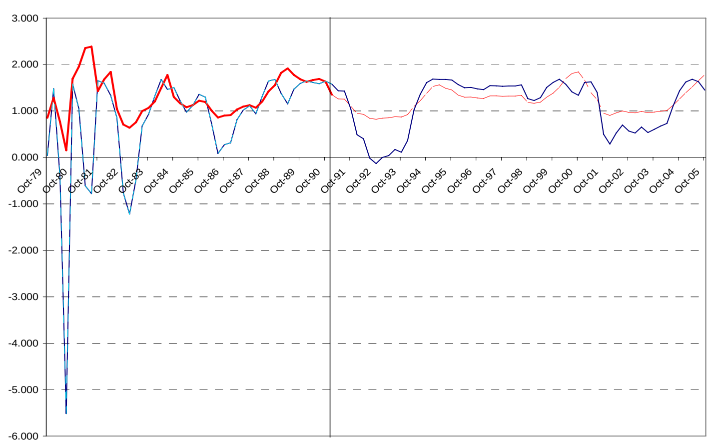


Fig. H.7. Inflation coefficient movement: Linear restriction on stock variable coefficient (12 lags IV)

(Tests for Stability of Coefficients across Sub-periods: *Case of 13 lags IV*)

(i) General Model: Dummy variables for all coefficients. Over-identification: 73 - 18 = 55

$$E(e_t Z_t) = E\{[R_t - \rho D_1 R_{t-1} - (1-\rho D_1)\{D_1\theta + (\alpha_0 + \alpha_1\delta_t + \alpha_2\delta_t^2)D_1\pi_{t+k} + \beta D_1 y_{t+k} + (\gamma_0 + \gamma_1\delta_t + \gamma_2\delta_t^2)D_1 s_t\} - \rho D_2 R_{t-1} - (1-\rho D_2)\{D_2\theta + (\alpha_0 + \alpha_1\delta_t + \alpha_2\delta_t^2)D_2\pi_{t+k} + \beta D_2 y_{t+k} + (\gamma_0 + \gamma_1\delta_t + \gamma_2\delta_t^2)D_2 s_t]\, Z_t\} = 0$$

$$\text{where } (D_1)' = [1\,1\cdots, 0\,0\cdots 0] \quad (D_2)' = [0\,0\cdots 0, 1\,1\cdots 1]$$

	α_0	α_1	α_2	β	ρ	θ	γ_0	γ_1	γ_2	*J-statistic*
1979:4 – 1991:1	1.230 (0.057)	0.260 (0.017)	0.006 (0.002)	0.065 (0.097)	0.549 (0.028)	4.431 (0.276)	-0.010 (0.005)	0.004 (0.003)	0.001 (0.002)	37.395 [0.9926]
1991:2 – 2005:4	1.902 (1.080)	0.497 (0.084)	-0.392 (0.193)	-0.160 (0.345)	0.797 (0.082)	0.287 (2.373)	0.054 (0.024)	0.017 (0.018)	0.022 (0.015)	

Nonlinearity Test

Null: $\alpha_1^h = \alpha_2^h = \alpha_1^l = \alpha_2^l = \gamma_1^h = \gamma_2^h = \gamma_1^l = \gamma_2^l = 0$: p-value = 0.0000

Null: $\alpha_1^h = \alpha_1^l = \alpha_2^h = \alpha_2^l = 0$: p-value = 0.0000

Null: $\gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.5459

Wald Test for Stability of Coefficients

Null: $\alpha_0^h = \alpha_0^l, \alpha_1^h = \alpha_1^l, \alpha_2^h = \alpha_2^l, \beta^h = \beta^l, \rho^h = \rho^l, \theta^h = \theta^l, \gamma_0^h = \gamma_0^l, \gamma_1^h = \gamma_1^l, \gamma_2^h = \gamma_2^l$: p-value = 0.0000

Null: $\alpha_0^h = \alpha_0^l, \alpha_1^h = \alpha_1^l, \alpha_2^h = \alpha_2^l, \gamma_0^h = \gamma_0^l, \gamma_1^h = \gamma_1^l, \gamma_2^h = \gamma_2^l \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l$: p-value = 0.0000

Null: $\alpha_0^h = \alpha_0^l, \alpha_1^h = \alpha_1^l, \alpha_2^h = \alpha_2^l \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l$: p-value = 0.0007

Null: $\gamma_0^h = \gamma_0^l, \gamma_1^h = \gamma_1^l, \gamma_2^h = \gamma_2^l \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l$: p-value = 0.0000

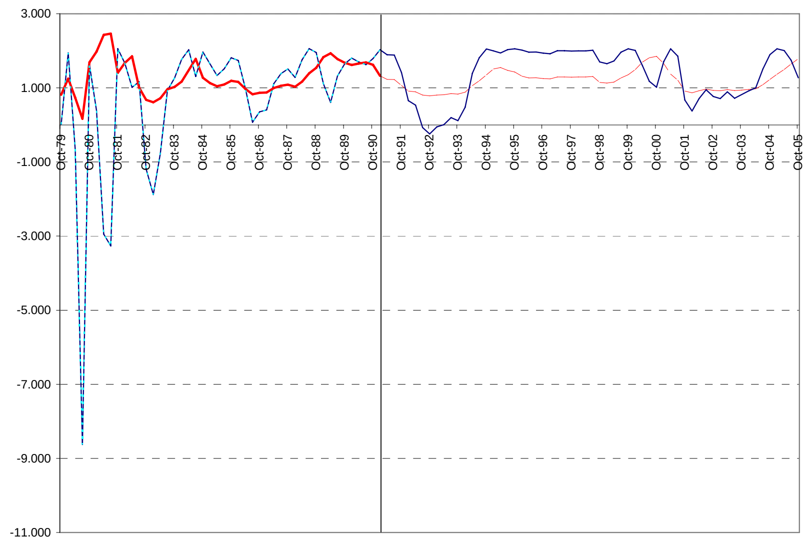


Fig. H.8. Inflation coefficient movement: General model (13 lags IV)

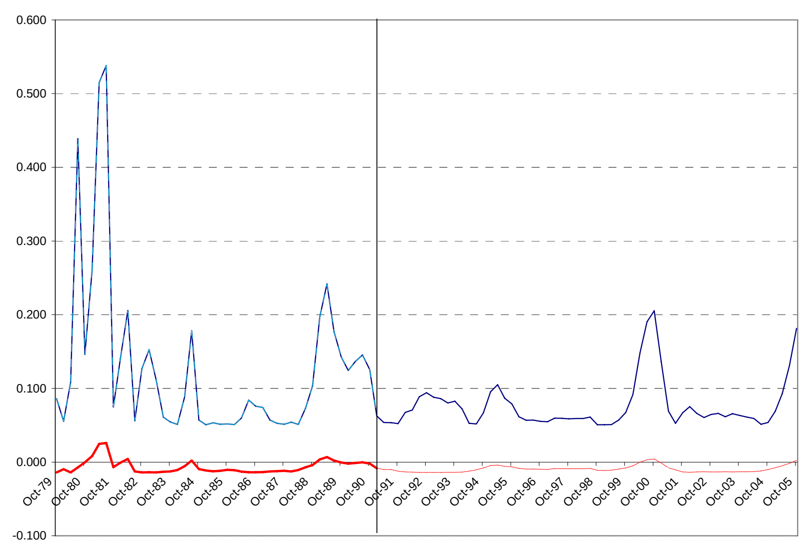


Fig. H.9. Stock variable coefficient movement: General model (13 lags IV)

(ii) Linear Restriction on Stock Variable Coefficient. Over-identification: 73-14 = 59

$$
\begin{aligned}
E(e_t Z_t) = E\{[R_t - \rho D_1 R_{t-1} - (1-\rho D_1)\{D_1\theta + (\alpha_0 + \alpha_1\delta_t + \alpha_2\delta_t^2)D_1\pi_{t+k} + \beta D_1 y_{t+k} \\
+ \gamma_0 D_1 s_t\} - \rho D_2 R_{t-1} - (1-\rho D_2)\{D_2\theta + (\alpha_0 + \alpha_1\delta_t + \alpha_2\delta_t^2)D_2\pi_{t+k} + \beta D_2 y_{t+k} \\
+ \gamma_0 D_2 s_t]\, Z_t\} = 0
\end{aligned}
$$

where $(D_1)' = [1\,1\cdots, 0\,0\cdots 0] \quad (D_2)' = [0\,0\cdots 0, 1\,1\cdots 1]$

	α_0	α_1	α_2	β	ρ	θ	γ_0	*J-statistic*
1979:4 –	1.249	0.260	0.005	0.092	0.552	4.366	-0.012	
1991:1	(0.053)	(0.016)	(0.002)	(0.087)	(0.026)	(0.268)	(0.007)	37.126
1991:2 –	1.584	0.524	-0.234	-0.294	0.769	0.693	0.065	[0.9979]
2005:4	(0.662)	(0.055)	(0.089)	(0.266)	(0.056)	(1.400)	(0.011)	

Nonlinearity Test

Null: $\alpha_1^h = \alpha_2^h = \alpha_1^l = \alpha_2^l = 0 \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l, \gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.0000

Null: $\alpha_1^h = \alpha_2^h = 0 \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l, \gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.0000

Null: $\alpha_1^l = \alpha_2^l = 0 \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l, \gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.0000

Wald Test for Stability of Coefficients

Null: $\alpha_0^h = \alpha_0^l, \alpha_1^h = \alpha_1^l, \alpha_2^h = \alpha_2^l, \beta^h = \beta^l, \rho^h = \rho^l, \theta^h = \theta^l, \gamma_0^h = \gamma_0^l \mid \gamma_1^h = \gamma_2^h = \gamma_1^l = \gamma_2^l = 0$: p-value = 0.0000

Null: $\alpha_0^h = \alpha_0^l, \alpha_1^h = \alpha_1^l, \alpha_2^h = \alpha_2^l, \gamma_0^h = \gamma_0^l \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l, \gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.0000

Null: $\alpha_0^h = \alpha_0^l, \alpha_1^h = \alpha_1^l, \alpha_2^h = \alpha_2^l \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l, \gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.0000

Null: $\gamma_0^h = \gamma_0^l \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l, \gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.0000

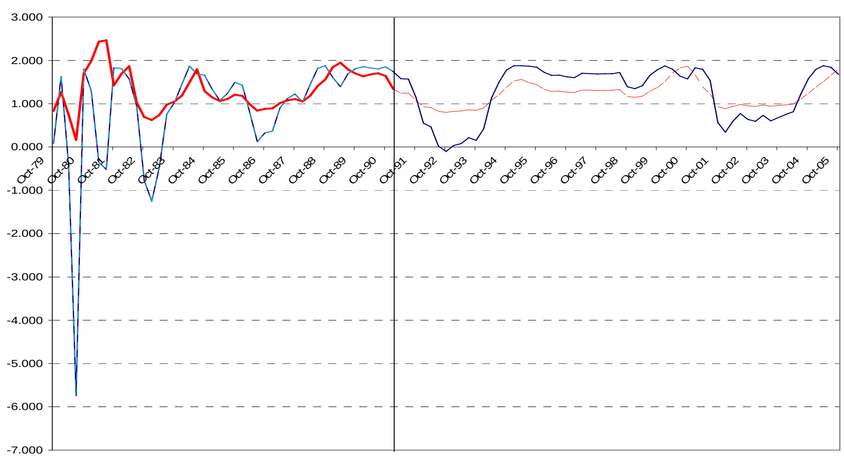


Fig. H.10. Inflation coefficient movement: Linear restriction on stock variable coefficient (13 lags IV)

(Tests for Stability of Coefficients across Sub-periods: *Case of 14 lags IV*)

(i) General Model: Dummy variables for all coefficients. Over-identification: 79 - 18 = 61

$$E(e_t Z_t) = E\{[R_t - \rho D_1 R_{t-1} - (1-\rho D_1)\{D_1\theta + (\alpha_0 + \alpha_1\delta_t + \alpha_2\delta_t^2)D_1\pi_{t+k} + \beta D_1 y_{t+k}$$
$$+ (\gamma_0 + \gamma_1\delta_t + \gamma_2\delta_t^2)D_1 s_t\} - \rho D_2 R_{t-1} - (1-\rho D_2)\{D_2\theta + (\alpha_0 + \alpha_1\delta_t + \alpha_2\delta_t^2)D_2\pi_{t+k}$$
$$+ \beta D_2 y_{t+k} + (\gamma_0 + \gamma_1\delta_t + \gamma_2\delta_t^2)D_2 s_t]\, Z_t\} = 0$$
$$\text{where } (D_1)' = [1\,1\cdots, 0\,0\cdots0] \quad (D_2)' = [0\,0\cdots0, 1\,1\cdots1]$$

	α_0	a_1	α_2	β	ρ	θ	γ_0	γ_1	γ_2	J-statistic
1979:4 – 1991:1	1.354 (0.055)	0.262 (0.011)	0.002 (0.001)	0.075 (0.053)	0.568 (0.018)	3.834 (0.273)	-0.005 (0.004)	0.0002 (0.002)	-0.0000 (0.002)	36.124 [0.9993]
1991:2 – 2005:4	0.696 (0.351)	0.519 (0.034)	-0.204 (0.072)	-0.314 (0.157)	0.732 (0.042)	2.657 (0.803)	0.047 (0.012)	0.012 (0.007)	0.015 (0.006)	

Nonlinearity Test

Null: $\alpha_1^h = \alpha_2^h = \alpha_1^l = \alpha_2^l = \gamma_1^h = \gamma_2^h = \gamma_1^l = \gamma_2^l = 0$: p-value = 0.0000

Null: $\alpha_1^h = \alpha_1^l = \alpha_2^h = \alpha_2^l = 0$: p-value = 0.0000

Null: $\gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.0273

Wald Test for Stability of Coefficients

Null: $\alpha_0^h = \alpha_0^l, \alpha_1^h = \alpha_1^l, \alpha_2^h = \alpha_2^l, \beta^h = \beta^l, \rho^h = \rho^l, \theta^h = \theta^l, \gamma_0^h = \gamma_0^l, \gamma_1^h = \gamma_1^l, \gamma_2^h = \gamma_2^l$: p-value = 0.0000

Null: $\alpha_0^h = \alpha_0^l, \alpha_1^h = \alpha_1^l, \alpha_2^h = \alpha_2^l, \gamma_0^h = \gamma_0^l, \gamma_1^h = \gamma_1^l, \gamma_2^h = \gamma_2^l \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l$: p-value = 0.0000

Null: $\alpha_0^h = \alpha_0^l, \alpha_1^h = \alpha_1^l, \alpha_2^h = \alpha_2^l \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l$: p-value = 0.0000

Null: $\gamma_0^h = \gamma_0^l, \gamma_1^h = \gamma_1^l, \gamma_2^h = \gamma_2^l \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l$: p-value = 0.0000

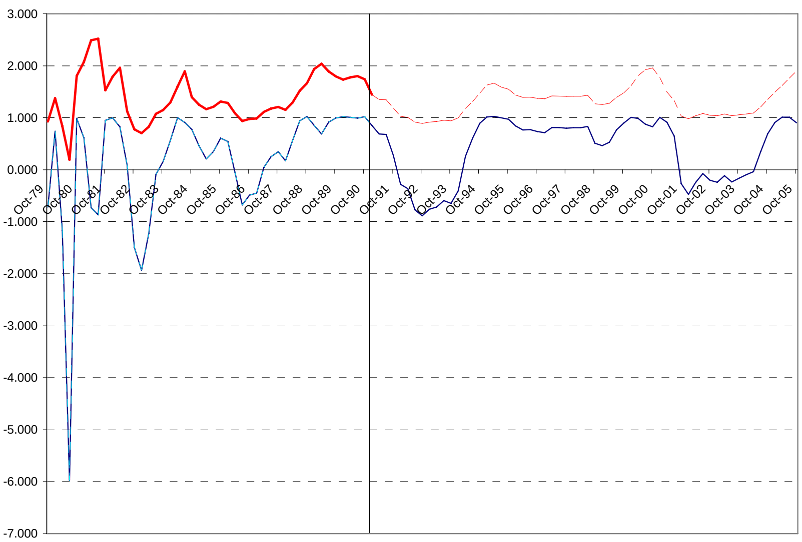


Fig.H.11. Inflation coefficient movement: General model (14 lags IV)

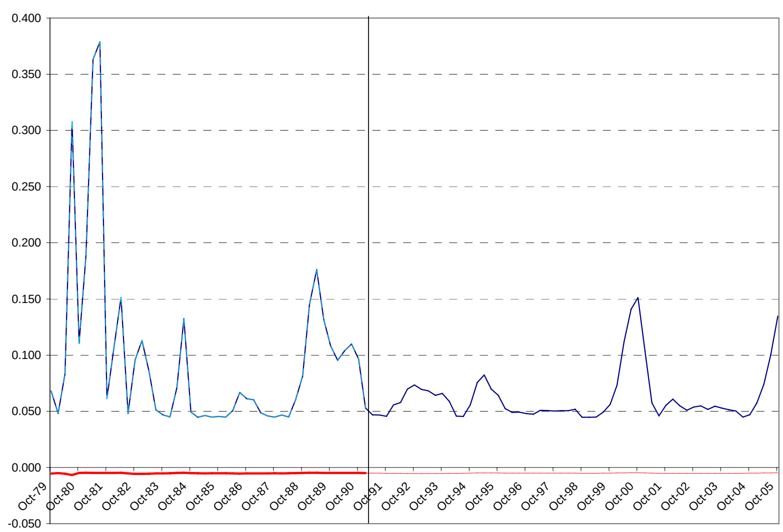


Fig. H.12. Stock variable coefficient movement: General model(14 lags IV)

(ii) Linear Restriction on Stock Variable Coefficient. Over-identification: 79-14 = 65

$$
\begin{aligned}
E(e_t Z_t) = E\{[R_t - \rho D_1 R_{t-1} - (1-\rho D_1)\{D_1\theta + (\alpha_0 + \alpha_1\delta_t + \alpha_2\delta_t^2)D_1\pi_{t+k} + \beta D_1 y_{t+k} \\
+ \gamma_0 D_1 s_t\} - \rho D_2 R_{t-1} - (1-\rho D_2)\{D_2\theta + (\alpha_0 + \alpha_1\delta_t + \alpha_2\delta_t^2)D_2\pi_{t+k} + \beta D_2 y_{t+k} \\
+ \gamma_0 D_2 s_t]\, Z_t\} = 0
\end{aligned}
$$

where $(D_1)' = [1\,1\cdots,\,0\,0\cdots0] \quad (D_2)' = [0\,0\cdots0,\,1\,1\cdots1]$

	α_0	α_1	α_2	β	ρ	θ	γ_0	*J-statistic*
1979:4 – 1991:1	1.354 (0.044)	0.262 (0.010)	0.002 (0.001)	0.077 (0.044)	0.568 (0.016)	3.838 (0.239)	-0.006 (0.002)	56.377 [0.8973]
1991:2 – 2005:4	0.680 (0.312)	0.542 (0.032)	-0.126 (0.035)	-0.376 (0.142)	0.717 (0.028)	2.555 (0.664)	0.055 (0.005)	

Nonlinearity Test

Null: $\alpha_1^h = \alpha_2^h = \alpha_1^l = \alpha_2^l = 0 \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l, \gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.0000

Null: $\alpha_1^h = \alpha_2^h = 0 \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l, \gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.0000

Null: $\alpha_1^l = \alpha_2^l = 0 \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l, \gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.0000

Wald Test for Stability of Coefficients

Null: $\alpha_0^h = \alpha_0^l, \alpha_1^h = \alpha_1^l, \alpha_2^h = \alpha_2^l, \beta^h = \beta^l, \rho^h = \rho^l, \theta^h = \theta^l, \gamma_0^h = \gamma_0^l \mid \gamma_1^h = \gamma_2^h = \gamma_1^l = \gamma_2^l = 0$: p-value = 0.0000

Null: $\alpha_0^h = \alpha_0^l, \alpha_1^h = \alpha_1^l, \alpha_2^h = \alpha_2^l, \gamma_0^h = \gamma_0^l \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l, \gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.0000

Null: $\alpha_0^h = \alpha_0^l, \alpha_1^h = \alpha_1^l, \alpha_2^h = \alpha_2^l \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l, \gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.0000

Null: $\gamma_0^h = \gamma_0^l \mid \beta^h \neq \beta^l, \rho^h \neq \rho^l, \theta^h \neq \theta^l, \gamma_1^h = \gamma_1^l = \gamma_2^h = \gamma_2^l = 0$: p-value = 0.0000

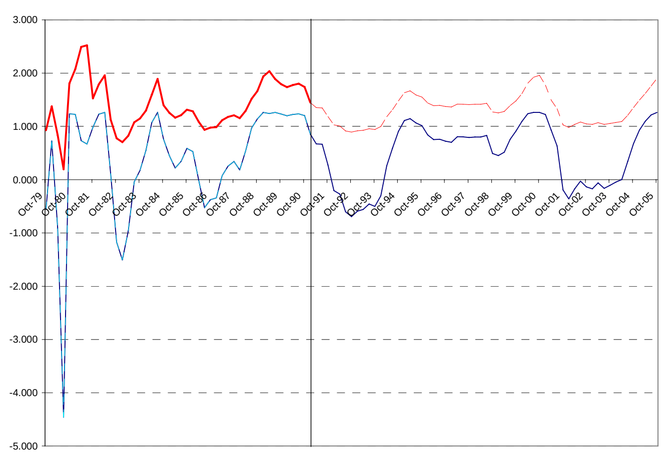


Fig. H.13. Inflation coefficient movement: Linear restriction on stock variable coefficient (14 lags IV)

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