Evidence Uncovered: Long-Term Interest Rates, Monetary Policy, and the Expectations Theory

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Abstract

This paper asks whether the expectations theory of the term structure holds conditional on an exogenous change in monetary policy. We argue that much of the previous work on the unconditional expectations theory as well as the empirical literature on monetary policy has failed to sufficiently account for simultaneous interactions between monetary policy and financial markets in the determination of interest rates. While the expectations theory predicts that policy affects long rates by influencing expectations of future short rates, it is also true that policy makers monitor bond markets for information on market expectations. We disentangle these interactions and obtain evidence strongly consistent with the expectations theory conditional on an exogenous change in monetary policy. We show that the marginal effect of our consideration for this source of simultaneity bias is significant in uncovering evidence for the theory.

Keywords:term structure, vector autoregression, interest rate smoothing, policy regimes,Bayesian VAR

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1. Introduction[1]

Despite ongoing debate over its validity in U.S. data.[2], the expectations theory of the term structure remains a fundamental building block of macro models which allow for the endogenous determination of interest rates of multiple maturities. Similar assumptions about term structure determination also pervade monetary policy discussions.[3]

The expectations theory takes on special relevance for policy makers because it implies ability to effect long term interest rates through influence on the expected path of short-term rates.[4] The existence of a term structure channel for monetary policy means that policy directly affects a wider array of private decision rules important in aggregate demand, while a predictable relationship between long term rates and expected future short rates ensures that this channel is manageable. Moreover, a variety of alternative policy actions or non-actions now become potentially helpful in achieving policy goals, including policy statements, speeches by policy makers, or anything else that effects market expectations of the path of future short term interest rates independly from the current short rate, possibly including the path of money growth.

This paper focuses on a conditional form of the expectations theory. It asks whether long-term interest rate responses to an exogenous change in monetary policy are well predicted by the

[1] I benefited greatly from discussions with Marvin Goodfriend, Jon Faust, Eric Leeper, John Rogers, and Jonathan Wright as well as comments from participants at the Midwest Macro Conference (Atlanta Fed) and workshops at the Board of Governors and the Riksbank. Thanks also to Tao Zha and Jon Faust for providing computer code. The views in this paper are solely the responsibility of the author and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or of any other person associated with the Federal Reserve System.

[2] Some of the works in this large literature include Campbell and Shiller(1991 and 1987), Hansen and Sargent(1980), Sargent(1979), Roberds, Runkle, and Whiteman (1996), Dejong and Whiteman(1996), and more recently, Favero(2001), and Bekaert and Hodrick(2000).

[3] Shiller, Campbell, and Schoenholtz (1983) made the following tongue-in-cheek remark:"...the theory seems to reappear perennially in policy discussions as if nothing happened to it...We are reminded of the Tom and Jerry cartoons that precede feature films at movie theatres. The villain, Tom the cat, may be buried under a ton of boulders, blasted through a brick wall (leaving a cat shaped hole), or flattened by a steamroller. Yet seconds later he is up again plotting his evil deeds." pg. 175

[4] Goodfriend (1998) discusses the usefulness of the term structure to policy makers. Akhtar(1995) motivates the need for structural models of the relationship between policy and long term interest rates from a policy perspective.

expectations theory.

Isolating the variance in long rates that is conditional on exogenous monetary policy is a non-trivial task. Although a recent literature has managed to isolate the qualitative effects of exogenous monetary policy using structural vector auto-regressive techniques, there exist many specifications of policy behavior (or policy rules) that are equally well supported by the data.[5] Different specifications of policy typically yield different quantitative predictions for the dynamic paths of macro and policy variables following a policy shock, yet quantitative accuracy in the estimation of long and short rate dynamics is likely important to uncovering evidence on the expectations theory. In this case, failure to recognize the sensitivity of estimated interest rate responses to the specification of policy behavior could lead to false negative conclusions about the theory's validity.

This paper avoids such false negative conclusions by searching across a subset of qualitatively reasonable models of monetary policy to see if any model closely matches the predictions of the expectations theory. By conducting a more comprehensive search than conventional structural VAR approaches which typically rely on a single or small finite set of specifications, we are more likely to find evidence in support of the theory, if it exists. If, on the other hand, deviations from the theory are found to be large across the entire subset of policy specifications we consider, the breadth of our search provides convincing evidence against the theory.

In the end, we find a number of reasonable policy specifications that predict long rate responses consistent with the theory following an exogenous change in policy. In the absence of a widely accepted theory of Federal Reserve behavior that would allow us to better identify actual policy behavior, the policy specifications uncovered in this paper in support of the expectations theory are as reasonable as the many specifications in the policy literature with similar qualitative predictions

[5] See Leeper, Sims, Zha(1996) and Christiano, Eichenbaum, Evans(1998) for overviews of literature that estimates the effects of an exogenous change in monetary policy in a structural vector auto-regressive framework.

and equivalent fits to the data.[6]

The approach used in this paper also allows a potentially important improvement on other studies of the effects of monetary policy on financial market variables: it allows us to avoid restrictive recursive assumptions in modeling the determination of long and short term interest rates.

While the expectations theory predicts that policy affects long rates by influencing expectations of future short rates, it is also true that policy makers monitor bond markets for information on market expectations. Policy responses to information in the term structure create simultaneities in the determination of short- and long-term interest rates, and thereby a potential source of bias in empirical models of interest rates. Much of the literature on the expectations theory as well as that on monetary policy neglects this possibility, applying or assuming recursive specifications of interest rate determination. We examine in detail whether consideration of the potential simultaneities between policy and bond markets has marginal importance in uncovering evidence on the conditional expectations theory and find that it does.

Lastly, our results contrast with previous hypotheses that empirical failures of the unconditional expectations theory are related to monetary policy behavior. Mankiw and Miron(1986) were the first to argue that interest rate smoothing by the Fed reduces agents' unconditional expectations of future short rate variation, and thereby the proportion of ex-post long-rate variation resulting from arbitrage activity under the theory. As a result, the authors argue, the unconditional variation in long rates is dominated by, albeit small, variation in the term premium.[7] Separately, Hamilton(1988) and Fuhrer(1996) have argued that the existence of historical policy regime changes

[6] The methods used in this paper obtain underidentified systems, making full model, goodness of fit measures inappropriate. We will evaluate the appropriateness of our identication by judging the impulse responses on qualitative consistency with those in the empirical literature on monetary policy.

[7] Other literature deriving from Mankiw and Miron's hypothesis include: Roberds, Runkle and Whiteman(1996), Rudebusch(1995), and Dotsey and Otrok(1995)

create nonlinearities in the data which can not be captured in the type of full sample, linear models, typically used to test the expectations theory. As we will see, these arguements do not apply in the conditional case examined in this paper, raising questions about their validity in the unconditional case.

The rest of this paper is structured as follows. The next section describes how we isolate the policy and non-policy related components of long rate variation in a VAR framework. Section 3 presents our main results on the conditional expectations theory. In section 4 we analyze the significance of our consideration of policy and bond market simultaneities in obtaining these results. Section 5 concludes.

2. Isolating Monetary Policy

A common method of structural VAR identification seeks to identify the effects of an exogenous one-time change in policy by appropriately restricting the decomposition of the contemporaneous variance covariance matrix of one step ahead forecast errors from a reduced form VAR:

$$E(\mu_t \mu_t') = \Sigma_\mu; \qquad \text{where } \mu_t = \ B(L) y_t. \tag{2.1}$$

Here y_t is an $mx1$ vector of macro economic time series, $B(L) = \sum_{i=0}^{p} B_i L^i$, and $B_0 = I$. The identifying restrictions on Σ_μ reflect assumptions about the contemporary behavioral relationships among the variables in y_t that are believed to hold in the structural model underlying the data which can be approximated as:

$$A(L) y_t = \nu_t \tag{2.2}$$

where $A(L)$ is a different matrix polynomial in L, and $\Sigma_v = I$. Equations 2.1 and 2.2 imply a mapping between the one step ahead forecast errors and the structural shocks:

$$\mu_t = A_0^{-1} \nu_t \tag{2.3}$$

which in turn yields a moving average representation of y_t as a function of current and past structural errors:

$$y_t = R(L)\nu_t \tag{2.4}$$

where we estimate $R(L) = B(L)^{-1}A_0^{-1}$. Including appropriate interest rate and money aggregate variables in y_t, one can then restrict the decomposition of $\widehat{\Sigma_\mu}$ in such a way that equation 2.3 obtains a money demand and monetary policy shock associated with a money demand and monetary policy equation in 2.2. The deterministic component of the policy equation in 2.2 in this way estimates systematic policy behavior while the policy shock captures a typical, idiosyncractic, exogenous change in policy. Equation 2.4.can then be used to simulate the variable impulse responses to an exogenous shift in the policy equation , $\nu_{MP} \in \nu_t$.

2.1. The Conditional Expectations Theory

Estimation of the effects of monetary policy using conventional identified VAR methods typically requires a minimum number of coefficient restrictions that is larger than that the set implied from theoretical models.[8] For many purposes this poses little difficulty since many sets of identifying restrictions have been found to obtain qualitatively robust predictions for the effects of monetary policy on macro variables.[9] In the present context however, quantitative accuracy in the estimation of long and short rate dynamics likely plays a very important role in uncovering evidence on the expectations theory. Thus reliance on any particular set of identifying restrictions could potentially lead to false negative conclusions.

[8] By symmetry of Σ_μ, the assumption that $\varepsilon_t\varepsilon_t' = I$ implies that there must be no more than $m(m-1)/2$ free parameters in A_0 such that

$$\Sigma_\mu = A_0^{-1}A_0^{-1'}$$

[9] Again, see Leeper, Sims, and Zha(1996) and Christiano, Evans and Eichenbaum(1998) for a review of the literature.

Faust(1998) provides an alternative approach to policy identification which allows the researcher to learn what inferences are supported by the data while only requiring a minimum number of prior assumptions about the shape and sign of the variable responses to an estimated shock. This approach allows us to examine a broad class of identified models which are consistent with conventional views about the effects of policy —those predicting a decline in output, prices and money following a policy shock which raises the federal funds rate– to evaluate the data fit with respect to the conditional expectations theory.

More specifically, we solve the following constrained minimization problem:

$$\min{}_{\alpha} \ \frac{1}{h}\sum_{t=0}^{h-1}\left(\widehat{R_t^n\alpha} - \frac{1}{k}\sum_{j=0}^{k-1}\widehat{R_{t+j}^m\alpha}\right)^2 \tag{2.5}$$

$$s.t. \qquad C^R\alpha \geq 0 \tag{2.6}$$

$$\alpha'\alpha = 1. \tag{2.7}$$

where $\widehat{R_t^n\alpha}$ and $\widehat{R_t^m\alpha}$ are the responses of the long and short rates to the policy shock $\alpha'\varepsilon_t$, formed as the optimal linear combination of orthogonalized shocks $\varepsilon_t = H^{-1}\mu_t$, obtained from a Cholesky decomposition of $\widehat{\Sigma_\mu} = HH'$. The matrix C^R defines a rxm set of linear restrictions on the impulse response functions $C(L)\alpha$, where $C(L)$ is the generic moving average representation associated with $\varepsilon_t : C(L) = B(L)^{-1}H$. Most importantly, $C^R\alpha \geq 0$ is a minimum set of restrictions sufficient to obtain reasonable impulse response functions.[10] The restriction that α has unit length maintains the normalization of error variance to unity.[11] We set h, a predetermined time horizon, equal to 48 months as in Faust (1998).

[10] Note that $C^R\alpha \geqq 0$ need not be neccessary conditions. Having obtained impulse response functions that are consistent with our priors about policy, relaxation of any of the non-necessary restrictions in $C^R\alpha$ can only improve the value of the objective function and thus obtain an even closer fit to the expectations theory conditional on monetary policy.

[11] For more information on the Faust method see Faust (1998) and previous draft of this paper (International Finance Discussion Paper #712).

We also perform a similar exercise expressing the expectations theory in terms of the long- short spread and expected changes in the short rate

$$\min_{\alpha} \ \frac{1}{h}\sum_{t=0}^{h-1}\left(\widehat{S_t^{n,m}}\alpha - \frac{1}{k}\sum_{j=0}^{k-1}(\widehat{R_{t+j}^{m}}\alpha - \widehat{R_t^{m}})\right)^2 \tag{2.8}$$

$$s.t. \qquad C^R\alpha \geq 0 \tag{2.9}$$

$$\alpha'\alpha = 1. \tag{2.10}$$

where $\widehat{S_t^n\alpha}$ is the spread between the long and short rate , and S_t^n is included directly in the VAR in place of R_t^n. This specification provides a potentially more powerful test of the expectations theory than that based on 2.5 - 2.7 in the presence of highly persistent interest rate processes.[12]

Defined in this way, problems 2.5 - 2.7 and 2.8 - 2.10 identify specifications of the data which: (1) predicts qualitatively reasonable variable responses to a policy shock; and (2) have the best fit with the conditional expectations theory in the sense that they have the smallest root mean squared premium deviation (RMPD) conditional on the policy shock.

A further advantage is that by searching over the full set of specifications satisfying $C^R\alpha \geq 0$, we can be reasonably certain that if the data supports the expectations theory conditional on policy, this approach is very likely to find evidence supporting it. If, on the other hand, it turns out that the minimum mean squared premium deviations obtained are nonetheless substantial, we will have robust evidence against the theory based on an extensive search of possible policy specifications.[13]

Lastly, to account for parameter uncertainty we perform the same optimization problem for

[12] We specify the theory in this form on the advise of a referee and in order for easier comparison with a large part of the literature on the expectations theory. Note that unlike much of the expectations theory literature which accounts for potential non-stationarity in the underlying series by specifying the VAR in terms of interest rate spreads and differences, we instead implement the Sims Zha(1998) prior of unit roots and co-integration. Importantly, with the use of this prior, the specification in 2.5 - 2.7 fully allows for cointegration between the levels of the macroeconomc and financial variables, while the specification in 2.8 - 2.10 does not.

[13] In section 3.2 below we consider the procedure's power to reject the theory when false.

each of 1000 draws from a simulated distribution of the reduced form parameters.[14] Since the resulting distribution is based on estimates from an underidentified model (2.5 - 2.7 and 2.8 - 2.10 provide the impulse responses to only one shock), it requires careful interpretation. In particular, the variation in RMPD is a function of specification uncertainty as well as parameter uncertainty. Understood correctly, the probability intervals derived in this way represent a range for the *lower bound* of the mean squared premium deviations across all specifications satisfying $C^R\alpha \geq 0$.

2.2. The Empirical Model

Following examples in the literature [Leeper, Sims, Zha(1996),Bernanke and Mihov (1998), Christiano, Eichenbaum, and Evans (1998), Leeper and Zha (2001)], we model the monetary economy with a parsimonious set of variables including: monthly interpolated real GDP (Y)[15], consumer prices (P),M2 (M2), and the overnight federal funds rate(RF). We also include a one month rate which we use for R^m, and either a long-term interest rate, R^n–alternatively represented with annualized rates on zero coupon bonds with maturities of $n = 2$ to 120 months—or $S_t^{n,m} = R^n - R^m$.[16] The data are in monthly frequencies taken from 1959:1 to 1995:12 with the non-interest rate series in logs. The interest rate data up to 1991:2 is from the McCulloch and Kwon data set and the remainder from Bliss(1996).[17] These data are pure discount (zero coupon) bond yields for U.S.

[14] Our procedure follows that in Faust and Rogers(1999). See Appendix A for details on how we generate the error bands using Monte Carlo simulation.

[15] By using interpolated GDP we are inadvertently including some information about future GDP in the output series. While monthly industrial production data provides an alternative to this problem, we preferred to use the former as more complete measure of aggregate output. Leeper and Zha(2001) performed the monthly interpolation of GDP.

[16] Simulations from earlier versions of this paper also encorporated commodity prices and a narrow money aggregate, total reserves, as these variable are often included in identified VAR models . In addition, we also looked at using only one short term rate: either the funds rate or the one month rate. We include some of these in the appendix of the paper (models C, D, and E in appendix D). The results presented here are consistent with those based on these alternative specifications.

[17] The long rate data from both sets was generously provided by Charles Evans from Evans and Marshall(1998). In that paper they perform diagnostics to determine that the data split is insignificant. The McColloch and Kwon data can be downloaded from the world wide web at http://www.econ.ohio-state.edu/mccull.html. with documentation found in " U.S. Term Structure Data, 1947-1992," Ohio State University Working Paper #93-6.

government securities that are adjusted for tax distortions and are continuously compounded.[18] The federal funds rate is continuously compounded and converted to a 365 day basis as described in Cook and Hahn (1991).[19]

Allowing for the presence of unit roots and cointegration in the data, we estimate the reduced form VAR parameters using the Sims Zha (1998) prior.[20] We also estimated the same VARs without a prior and found that, although the sufficient set of restrictions necessary to obtain reasonable impulse responses was often larger, the main findings of the paper were insensitive to the use of a prior. We refer the reader to the appendix for a presentation of these results (model A; appendix D). In the results presented here, the set of sufficient restrictions, $C^R\alpha$, is indeed small: we require that on impact of a contractionary policy shock, the federal funds rate responds positively, and M2, P, and Y respond negatively.

Lastly, all the models presented here include six lags unless otherwise noted. Model tests for lag lengths based on the Akaike Information Criterion(AIC) and Schwarz Criterion(SC) chose a lag length of two for all interest rate combinations. In a previous working paper we estimate a variety of models with two and six lags. The results were insensitive to lag length.[21]

Figure 1 presents the variable impulse responses for the minimum RMPD cases from each of four VARs estimated using a long rate with maturity of 6, 12, 36, 120 months. The solid and dashed lines are the median and 68 percent probability bands drawn from the posterior distribution for the impulse responses. Recall that the model structures underlying these distributions are not fully identified. This means that the error bands in figure 1 capture uncertainty about the non-policy

[18] A discussion of the need for continuous compounding and tax adjustment is found in the *Handbook of Monetary Economics*, 1990, Chapter 13. The Fama data was not tax adjusted. Marshall and Evans explain that tax adjustment was not an issue during the period sampled.

[19] See Appendix B for more details on specific series used.

[20] See appendix C for more information on the Sims Zha prior and on the method used to simultate the posterior distribution.

[21] Model D in Appendix D includes only two lags.

structure of the model as well as uncertainty about the location of both the policy and non-policy parameters.

The responses in figure 1 are fully consistent with conventional views about the qualitative effects of monetary policy and are similar to those found in the fully identified VAR literature. A contractionary policy shock leads to a 10 to 20 basis point increase in the funds rate which subsequently declines but remains above its initial value for at least 11 months. M2, Y, and P all gradually decline following the shock, with the error bands for M2 and Y falling everywhere below zero, while the error bands for P exhibit some probability of a small but persistent price puzzle. In further simulations (model B in appendix D) we include an additional restriction that the price response be negative in the third month after the shock and obtained results similar to those presented here except that the error bands for P are everywhere below zero.

The fifth and seventh rows of figure 1 display the long rate and term premia responses to the policy shock, the latter measured as the difference between the long rate response at each point in time and the average of the short rate responses over the k periods on and following the shock. In each case, the long rates increase initially but by less than the funds rate on impact of the shock and then fall back to, and sometimes below, their initial levels. The error bands all contain zero indicating that the sign of the response is not well identified. In all cases the premium response is negligible, responding by less than 1.5 points in the initial months following the shock, and then remaining near zero thereafter. The 68% error bands also contain zero throughout the 48 month horizon in all cases.

Figure 2 shows the impulse responses associated with the minimum RMPD case defined according to 2.8- 2.10. These show largely similar predictions for Y, P, and M2 as in those shown in figure 1, except that the response of the spreads shown in row 5 of figure 2 are more tightly identified than the long rate responses in figure 1.

The posterior median forecast error variance shares due to policy for the results in figures 1 and 2 are shown for R^m, R^n or $S_t^{n,m}, Y$, and P, in Table 1. The value are consistent with the common finding in the identified VAR literature that endogenous policy is more important than exogenous policy in determining the funds rate. The variance shares for R^n are similarly small. The variance shares for output are in line with the identified VAR literature but are smaller than those in Faust(1998) based on maximum variance share calculations similar to the minimum RMPD calculations in this paper.[22] However none of these forecast error variance shares are well identified: the 68% error bands from the posterior distributions often covered a very wide range, and in some cases nearly the full range of possible values from zero to one.

3. Measuring Fit with the Conditional Expectations Theory

Tables 2 and 3 presents three sets of statistics that more precisely measure fit with the conditional expectations theory, including point estimates as well as probability bands from the simulated posterior distributions All three are calculated using a 48 month horizon. Table 1 shows results from simulations when the expectations theory is expressed in levels and Table 2 shows results from simulations when the theory is expressed in spreads and short rate changes.

The first set of statistics in Tables 1 and 2 are just the square root of the optimal value of the criterion function from the problem in equations 2.5 - 2.7 (2.8- 2.10),respectively, and as such measure the average deviation in the premium over the full horizon. The second set of statistics measure the variance of the premium relative to the variance in the long rate (the long-short spread) (RV), both conditional on the policy shock. This statistic is useful as a measure of the proportion

[22] Faust (1998) performs robustness tests on this apparent consistency in the identified VAR literature and finds that identifications exist in which policy explains a majority share of the variance of output.

of the conditional variation in R^n ($S^{n,m}$) attributable to deviations in the premium. Since the RMPD and RV statistics are always positive, fit with respect to the theory should be evaluated on the basis of the intervals' proximity to zero rather than whether they contain zero. Lastly, following the advice of a referee, we report the variance ratio of the conditional "observed" long rate and the conditional theoretical long rate under the expectations theory:

$$\frac{\sigma_P}{\sigma_A} = \frac{var(\frac{1}{k}\sum_{j=1}^{k-1} R^1_{t+j}|\alpha'\varepsilon_t)^{\frac{1}{2}}}{var(R^n|\alpha'\varepsilon_t)^{\frac{1}{2}}} \text{ or } \frac{var(\frac{1}{k}\sum_{j=1}^{k-1}(R^m_{t+j} - R^m_t)|\alpha'\varepsilon_t)^{\frac{1}{2}}}{var(S^{n,m}_t|\alpha'\varepsilon_t)^{\frac{1}{2}}} \tag{3.1}$$

As such, $\frac{\sigma_P}{\sigma_A}$ is the conditional analogue to a statistic often reported in empirical expectations theory literature following Campbell and Shiller(1991).

In Table 1, we see that for all long rates considered, the point estimates of the RMPD are less than one half of one basis point and the premium variance accounts for less than 1 percent of the variance in the long rate. Results from the posterior distributions for these statistics indicate close proximity to zero. The 75th percentiles for the RMPD's are all less than 1 basis point and the largest 75th percentile for the RV's is a little over 5 percent, with the remainder near or below 2 percent.

The last column of Table 1 shows the point estimates and posterior distributions for $\frac{\sigma_P}{\sigma_A}$. The point estimates are all very near one, and the 95 percent probability intervals from the posterior distributions are often very narrow and centered near one. This compares with Campbell and Shiller's (1991) finding that the realized spread is significantly more variable than theoretically predicted for the same interest rate combinations.

Two possible reasons for the difference in our results versus Campbell and Shiller is that the theory holds conditional on monetary policy but not unconditionally, or that the information set used to model expected short-term rates in this paper is somehow more informative about actual expectations than the limited information (bivariate) set used by Campbell and Shiller(1991). Favero(2002) argues that the Campbell and Shiller results could be improved by the inclusion of other macroeconomic variables in the information set used to model interest rate expectations. In that paper he performs a full information test of this nature which also allows for time variation in the formation of short rate expectations and finds evidence in support of the unconditional expectations theory. This paper also models short rate expectations using a fuller set of information than that in Campbell and Shiller, however unlike Favero, we do not allow for time variation in the model parameters.

Table 2 shows the results when the expectations theory is instead expressed in terms of $S_t^{n,m}$ and expected changes in R^m. With a few exceptions, these results are very similar to those based on problem 2.5-2.7 in Table 1. The exceptions are that the RV statistics are large when $n = 2$ and 3 months. Nonetheless, in these cases, the RMPD and $\frac{\sigma_P}{\sigma_A}$ statistics support the theory. Recall that in these cases, there are three relatively short interest rates: the fund rate, the one month rate and a two or three month rate. The proximity of the maturity of the three rates in these cases led us to consider whether the policy shock was indeed well isolated or whether the policy shock might contain some of the long rate responses to policy. In an effort to partially account for this possibility, we considered specifications that used the same long rates, but only one short rate, the funds rate or the 1 month rate, with the single short rate serving in the policy restrictions as well as the predictor for long rates. The results from a model using only the funds rate are included as models C, D, and E in appendix D. The same pattern arises however when the theory is expressed in terms of $S_t^{n,m}$ and expected changes in R^m.

3.1. Sensitivity Analysis

Figures 1 and 2 present a convincing argument in support of the conditional expectations theory based on impulse responses functions, we can also ask whether the policy equations implied by the optimal $\alpha's$ are consistent with that behavioral interpretation. Although researchers disagree on the relevance of interpreting particular VAR parameter estimates in these set-ups, because our examination of the implied policy equations in the models presented so far did not, in general, hold up to this type of scrutiny, we ran a further set of simulations which incorporated beliefs about the relative signs of the contemporaneous policy parameters in our prior.

Our methodology was to find a set of sign and shape restrictions on the variable impulse responses that was sufficient to obtain reasonable equilibrium paths for the variables following the shock, as well as reasonably signed coefficients for RF, M2, Y, and P in the contemporaneous policy equation implied by each optimal α :

$$\alpha' H^{-1} y_t = \alpha' \varepsilon_t \tag{3.2}$$

Specifically, we now also required that the coefficients on M2, P, and Y were of opposite sign to the coefficient on RF such that the implied policy equations took the form:

$$RF_t = f(\overset{+}{M}2, \overset{+}{Y}, \overset{+}{P}, 1mo, R^n)_t + \alpha' \varepsilon_t. \tag{3.3}$$

We did not restrict the sign on the coefficient on the one month rate or the long rate in $C^R\alpha$. Results for this model setup are shown under model A in appendix D where we also list the set of identifying restrictions sufficient to obtain reasonable specifications satisfying this set of priors. The first table in appendix D shows the premium variation statistics and their coverage intervals for each long rate case. Impulse responses to a policy shock were similar to those shown in

Figures 1 and 2. The long rate responses under this identification strategy again show remarkable consistency with the expectations theory. In this case the RMPD statistics are always below two basis points and account for, at most, 4 percent, and most often less than 2 percent, of the variation in long rates conditional on the policy disturbance. The last table shown for model A shows the contemporaneous policy parameters for each interest rate combination under this policy modeling strategy. The coefficients on R^n and the one month rate, which are freely estimated, are nearly equal and of opposite sign, suggesting that policy responds positively to the spread $S_t^{n,1}$.

In a previous version of the paper we selectively tested our results for sensitivity to subsampling by performing similar analyses on data from pre-1979 and post-1982, corresponding to breaks in Bernanke and Mihov(1998). Our conclusions about the expectations theory conditional on monetary policy were maintained in the subsample results. In particular, the RMPD in every case was below one basis point and the variance in the term premium accounted for less than five percent of the variation in the long rate in all but one case, when $n = 9mo$, in which case it accounts for nine percent or less.

3.2. Measuring Power

In this paper, we searched across the set of reasonable policy specifications to find the smallest premium response. We argue that evidence obtained in this way is informative about the predictive power of the expectations theory following a policy shock because our method does not preclude large premium deviations in the, albeit, minimum cases. However, this requires that our methods have sufficient power to reject the theory in the event that the theory does not hold.

To get sense for the power of our procedure , we re-solved 2.5- 2.7 specifying $C^R\alpha \geq 0$ as that sufficient to obtain impulse responses qualitatively consistent with a money demand shock

The literature on identifying money demand shocks in a VAR framework is much more limited than that on monetary policy. We based our prior sign and shape restrictions on the estimated variable responses to a money demand shock in Gali's(1992). In that paper the Fed is assumed to partially accommodate money demand shocks, such that a money demand shock is associated with a simultaneous rise in a nominal short-term interest rate (the 3 month T-bill rate) and a broad money aggregate (M1) on impact of the shock. Since the Fed only partial accommodates the increase in the demand for money, prices must fall in order to re-equilibrate real balances. This in turn limits the negative effect on output from the increase in the interest rate. Accordingly, we defined $C^R\alpha \geq 0$ as the set sufficient to obtain a decline in Y and P, and an increase in M2 and RF in response to $\alpha'\varepsilon_t$. We did not form any priors or place any restrictions on the behavior of the one-month or longer term interest rates. The set of sufficient restrictions for the alternative long rate cases are noted at the bottom of Table 4. Table 4 also reports the point estimates for RMPD, RV, and $\frac{\sigma_P}{\sigma_A}$ for the minimum cases obtained for each R^n simulation.

From Table 4 we see that the absolute size of the premium deviations following a demand shock are comparable to those conditional on a policy shock, but that relative to the size of the long rate response, the premium deviations are generally noticeably larger. When the long rate maturity is greater than 6 months, the variance in the premium accounts for more than 15 percent and as much as 46 percent of the variation in the long rate. Further, the ratio of the conditional predicted and actual variation in the long rate are substantially larger than one in all but one case, when $n = 4$ months. These preliminary findings suggest that the expectations theory fails conditional on a money demand shock. More important for the present analysis, the results in Table 4 demonstrate that the search algorithm used in this paper is capable of rejecting the theory when such an outcome is not supported by the data.

4. Does Simultaneity Matter?

Previous authors have looked at the effects of monetary policy on long-term interest rates. However much of this work ignores or insufficiently accounts for potential simultaneities between policy and the bond market. Most notably, Cook and Hahn(1989) measured the effect of policy on long rates by tracking their response to a change in the FOMC funds rate target. Because this data selection method fails to distinguish between rate changes that are endogenous responses by policy and those that are truly exogenous however, their results likely confuse the effects of policy with changes in the state of the economy to which policy was responding.[23] Evans and Marshall(1998) and Edelberg and Marshall(1996) use structural VAR methods to look at the effects of an exogenous policy shock on long-term interest rates. While these papers find mixed evidence on the conditional expectations theory, they make strong assumptions about the interaction between policy and the bond market by specifying policy behavior that does not respond directly to long-term bond rates. As a result, their estimates of long rate responses to a policy shock are potentially confused with policy responses to the bond market.[24]

In a previous version of this paper we contrasted our results, which do not restrict interacts between policy and the bond market, with results from recursive identifications motivated by specifications in Evans and Marshall(1998) and Edelberg and Marshall(1996). We found that the premia deviations were virtually always (and often substantially) smaller in the minimum RMPD

[23] Cook and Hahn also do not distinguish between anticipated and unanticipated changes in the funds target by the FOMC. Because anticipated changes in the short rate would likely be priced into long rates well before the two to three day time period surrounding the target change that they examine, the correlation between long and short rates within this period is an inaccurate measure of the effects of monetary policy.

[24] Edelberg and Marshall(1996) address the simultaneity problem indirectly by conditioning the policy shock on policy responses to commodity prices – which they posit contain the same information about inflation expectations as long bond rates. Their use of commodity prices in this manner has no theoretical justification however. In order to accurately isolate the correlation between long and short rates that is due to policy, the policy shock must be conditioned directly on policy responses to long rates. Evans and Marshall(1998) use the Christiano, Evans and Eichenbaum(1996) , Gali(1992), and Sims and Zha(1998a) identifications which do not allow for full simultaneity between long and short rates.

cases than in the recursive cases.

However a comparison of our results with those from a fully recursive specification can not accurately measure the marginal impact of our allowance for full interaction between policy and the bond market. While the specifications based on the Faust procedure are, in general, very limited in their recursive restrictions —meaning there are potentially multiple degrees of simultaneity through which our results are effected— the fully recursive specifications do not allow for simultaneity between any pair of variables. In addition, because the Faust algorithm obtains under-identified systems (it obtains impulse responses to only one shock), we can not use it to isolate the effect of any particular channel of simultaneity through the marginal inclusion of a recursive restriction.[25]

To get a better sense of the importance of bond market/policy simultaneity in obtaining our results, we conduct a series of experiments in a conventional, fully identified VAR framework following methods described in section 2. By moving to a fully identified framework we are able to vary the degree of simultaneity between policy and the bond market on the margin and trace out the effects for model fit with the expectations theory conditional on exogenous monetary policy.

Specifically, we first estimate a benchmark identified BVAR (again using the Sims Zha prior) in which policy is restricted from responding to long-term interest rates contemporaneously but in which long rates are allowed to respond to policy. We then re-estimate the system including a non-zero prior variance but zero prior mean for the parameter that measures the contemporaneous policy response to the long rate. This "soft zero" restriction allows for positive variation in the coefficient around a zero mean, in contrast to the "hard zero" restriction in the benchmark model

[25] This underidentification implies that the long rate paths from any two specifications can differ for an indeterminate number of reasons, making it impossible to isolate any particular source of variation across specifications. The specification of money demand, for example, is not pinned down using Faust's method and is therefore likely to vary between specifications that also differ in terms of monetary policy behavior.

which assumes a degenerate prior distribution around a zero prior mean.[26], [27]We then compare models based on different size assumptions about the prior variance on the coefficient on the long rate in the policy equation in terms of their fit with the conditional expectations theory to see if simultaneity is indeed important in generating our results in section 3.

Table 5 shows the contemporaneous benchmark model structure and estimated parameters, along with the respective 68 percent error bands for the parameters in parentheses. The important structural elements are that the funds rate and the level of the money stock are jointly determined by a money demand and monetary policy equation, with the latter specified to be unresponsive to the long rate.[28] The goods sector is not structurally specified and is unresponsive to the monetary sector within the month. Lastly, the financial sector is modeled with a one month rate and a long term interest rate that responds to all information in the system contemporaneously with the exception that the one month rate is recursive with respect to the long rate. Figure 4 shows the variable responses to the policy shock in the benchmark model when $n = 36mo$. All of the specifications estimated obtained qualitatively reasonable predictions for the effects of the policy shock in line with the results obtained using the Faust procedure and the existing empirical literature of the effects of monetary policy. Model diagnostic tests[29] including tests of the over-identifying restrictions where appropriate (in the benchmark model) and a comparison on of the variance covariance matrix of the historical structural shocks implied by the model against the orthogonality assumption did not reject this, or any of the specifications derived from this benchmark model. [30]

[26]See Leeper, Sims, Zha(1996) for other examples of BVAR's estimated with soft zero restrictions.

[27]See Appendix C for more information on the implementation of the Sims Zha prior and the soft zero restrictions.

[28]See Leeper and Roush(2003) for similar structural VAR specification and discussion of the role of simulateity between M and R.

[29]These test results are not included here due to space limitations but are available upon request.

[30]This outcome of multiple non-rejections reflects the generic underidentification of policy in the SVAR literature. Again, this underidentification motivated the approach to policy specification based on the Faust procedure in this paper.

Table 6 compares the RMPD and RV statistics for the benchmark specification with those from specifications which include a non-zero prior variance on the long rate parameter in the policy equation. In the latter cases, the prior variance is restricted to be a factor, μ_{R_L}, (respectively five and twenty-five percent) of the prior variances of the other contemporaneous parameters in the system. When $\mu_{R_L} > 0$, we should obtain non-zero estimates for this parameter if policy responses to the bond market are supported by the data. Alternatively, if the hard zero restriction in the benchmark model is indeed binding, then we should obtain non-zero estimates for this parameter when the prior is in this way relaxed. Then under the hypothesis that recognition of the simultaneity between policy and bond markets is important to uncovering evidence for the expectations theory, these non-zero estimates should in turn be associated with smaller premium deviations conditional on a policy shock.

From Table 6 we see that larger μ_{R_L} are consistently associated with lower premium deviations following a policy shock. The greatest improvement in fit with the expectations theory occurs when $n = 120mo$, with the RMPD falling from 1.78 basis points in the benchmark specification to less than one half of one basis point when $\mu_{R_L} = 0.25$, and RV falling from 32.54 percent to 5.61 percent. Improvement in terms of RMPD's is most statistically significant when the long rate under consideration is considerably long —when $\mu_{R_L} = 0.25$, the RMPD falls outside the benchmark 68 percent interval for $n > 12mo.$, and outside the 90 percent interval for $n > 36mo.$[31,32]

[31] The probability intervals reported in Table () are from simulated posterior distributions constructed according to methods outlined in Sims and Zha (1998b, 1999).

[32] While the relative variance values when $\mu_{R^n} > 0$ do not fall outside the 68% or 95% intervals from the benchmark specification, examination of these posteriors distributions shows them to have relatively fat tails. This may be the result of two factors. First, the posterior spread for both RMPD and Rel. Var. increase with n because they are based on impulse responses whose estimation precision decreases with the forecast horizon such that the premium for longer long rates are also less precisely estimated. Secondly, we might expect greater spread in the posterior for this statistic at all long rate maturities since it involves a ratio of variances making very small and very large values more probable - they can now result from either relatively small (large) numerators or relatively large (small) denominators.

This is consistent with the hypothesis that policy makers monitor the bond market as a source of information on intermediate and long term inflation and growth expectations.

5. Conclusion

The results in this paper demonstrate the existence of *structural,* data consistent, models of the U.S. economy in which long rate responses to an exogenous change in policy are closely predicted by the expectations theory. This finding is especially relevant to policy makers in that it provides support for a term structure channel of monetary policy. Further, our minimally restrictive approach to the empirical identification of monetary policy, ensures that this evidence is consistent with a broad class of policy specifications found in the current literature.

Perhaps the most important contribution of this paper is that we are able to find evidence for the expectations theory by breaking down the correlation between long and short rates into policy and non-policy related components. This approach required that we disentangle policy responses to the bond market from bond market responses to policy. Without a specific interest in measuring the effects of policy, however, it is not obvious why such a structural decomposition is relevant to the theory's performance since, in principle, it should hold conditional on all types of shocks. Simultaneities between policy and financial markets necessitate multiple equation econometric methods, but they do not require structural identification.

Yet the results in section 4 demonstrate that the performance of the expectations theory conditional on a monetary policy shock rests, in part, on the researcher's successful isolation of policy and non-policy effects on long rates. This evidence that structural identification is relevant to the theory is difficult to square with theoretical underpinnings of most reduced form tests of the expectations theory. Our results suggest that long rate movements in response to at least one type of non-policy shock lead to significant term premium deviations. Although very preliminary, our findings in section 3.2 suggest that money demand shocks could be one source of unconditional failure. Although beyond the scope of this paper, one can imagine a model in which the premium agents require to hold one debt instrument over a similar asset of different maturity is endogenously linked to financial innovation which shows up in the shock to money demand in an identified VAR.

Whether or not money demand shocks actually drive our result that structural identification matters for the theory, our results demonstrate that it is not monetary policy behavior that has induced failures in previous reduced form tests of the theory, as suggested by several authors mentioned in the introduction to this paper. The claims that short rate smoothing by the Fed or policy regime changes explain the recorded failures are inconsistent with the findings in this paper. Our results are derived from a non-parsimonious estimation of historical Fed behavior and yet find evidence of significant arbitrage activity consistent with the expectations theory following a policy shock. Similarly, if policy regime changes could alone explain the failure of the theory, then we should not have been able to uncover evidence for the theory conditional on any type of shock based on a linear model estimated from an unbroken data set.

Table 1: Forecast Error Variance Shares:

Panel A
SZ prior, ET in levels
Monetary System: $y_t = (Y_t, P_t, M2_t, RF_t, R^n_t, R^1_t)$

$\mathbf{R}^n$	1st mo.		48th mo			
	RF	$\mathbf{R}^n$	**RF**	$\mathbf{R}^n$	**Y**	**P**
2mo	.03	.04	.04	.03	.23	.05
3mo	.04	.04	.04	.03	.23	.05
4mo	.04	.04	.04	.03	.22	.05
6mo	.04	.04	.04	.03	.19	.05
9mo	.05	.04	.043	.031	.17	.06
12mo	.07	.04	.046	.035	.18	.05
24mo	.11	.04	.046	.025	.21	.03
36mo	.12	.03	.045	.021	.22	.03
48 mo	.12	.03	.044	.016	.24	.02
60 mo	.13	.02	.044	.013	.25	.02
120 mo	.12	.01	.040	.005	.21	.02

Panel B:
SZ prior, ET in differences
Monetary System: $y_t = (Y_t, P_t, M2_t, RF_t, R^n_t, R^1_t)$

$\mathbf{R}^n$	1st mo.		48th mo			
	RF	$\mathbf{R}^n$- $\mathbf{R}^1$	**RF**	$\mathbf{R}^n$- $\mathbf{R}^1$	**Y**	**P**
2mo	.02	.07	.03	.05	.04	.20
3mo	.10	.04	.02	.03	.20	.03
4mo	.06	.05	.04	.03	.23	.03
6mo	.06	.06	.04	.03	.24	.03
9mo	.09	.08	.04	.03	.25	.04
12mo	.07	.07	.04	.03	.23	.02
24mo	.08	.07	.06	.03	.23	.01
36mo	.08	.08	.03	.03	.20	.02
48 mo	.08	.09	.06	.03	.20	.01
60 mo	.08	.09	.03	.03	.20	.01
120 mo	.08	.10	.03	.06	.19	.02

Table 2: Measuring Conditional Fit: (SZ prior, ET in levels)
Monetary System: $y_t = (Y_t, P_t, M2_t, RF_t, R_t^n, R_t^1)$

$\mathbf{R}^n$	$C^R\alpha$	**RMPD(b.p.)**			**RV(%)**			$\frac{\sigma_P}{\sigma_A}$		
		Pt. Est.	Pdf		Pt. Est.	Pdf		Pt. Est.	Pdf	
2 mo	A	0.19	25%*	0.18	0.371	25%*		0.9847	5%*	0.9767
			50%	0.24		50%			50%	0.9993
			75%	0.30		75%			95%	1.0073
3 mo	A	0.29	25%	0.23	0.149	25%	0.053	0.9966	5%	0.9706
			50%	0.30		50%	0.150		50%	0.9991
			75%	0.40		75%	0.477		95%	1.0076
4 mo	A	0.30	25%	0.24	0.103	25%	0.068	0.9999	5%	0.9658
			50%	0.32		50%	0.192		50%	0.9989
			75%	0.42		75%	0.561		95%	1.0073
6 mo	A	0.19	25%	0.27	0.038	25%	0.091	0.9997	5%	0.9516
			50%	0.36		50%	0.238		50%	0.9982
			75%	0.48		75%	0.703		95%	1.0057
9 mo	A	0.16	25%	0.28	0.150	25%	0.099	0.9986	5%	0.9530
			50%	0.39		50%	0.272		50%	0.9980
			75%	0.54		75%	0.762		95%	1.0035
12 mo	A	0.26	25%	0.27	0.096	25%	0.097	0.9995	5%	0.9528
			50%	0.38		50%	0.266		50%	0.9980
			75%	0.54		75%	0.862		95%	1.0032
24 mo	A	0.31	25%	0.25	0.165	25%	0.138	0.9994	5%	0.9295
			50%	0.36		50%	0.375		50%	0.9976
			75%	0.49		75%	1.289		95%	1.0018
36 mo	A	0.29	25%	0.24	0.149	25%	0.154	0.9997	5%	0.9202
			50%	0.33		50%	0.432		50%	0.9974
			75%	0.45		75%	1.577		95%	1.0016
48 mo	A	0.26	25%	0.22	0.127	25%	0.162	0.9998	5%	0.9079
			50%	0.31		50%	0.521		50%	0.9969
			75%	0.42		75%	2.028		95%	1.0013
60 mo	A	0.23	25%	0.22	0.135	25%	0.182	0.9997	5%	0.9004
			50%	0.29		50%	0.632		50%	0.9964
			75%	0.40		75%	2.518		95%	1.0006
120 mo	A	0.15	25%	0.18	0.159	25%	0.279	0.9995	5%	0.7956
			50%	0.24		50%	1.351		50%	0.9933
			75%	0.32		75%	5.185		95%	1.0002

* From simulated posterior distribution based on 1000 draws

RMPD $= [\frac{1}{48}\sum_{t=0}^{47}[R_t^n - \frac{1}{k}\sum_{j=1}^{k-1} R_{t+j}^1)]^2]^{\frac{1}{2}}$
RV. $= \frac{var(premium|\alpha'\varepsilon_t)}{var(R^n|\alpha'\varepsilon_t)} * 100\%$
$\frac{\sigma_P}{\sigma_A} = \frac{var(\frac{1}{k}\sum_{j=1}^{k-1} R_{t+j}^1)|\alpha'\varepsilon_t)^{\frac{1}{2}}}{var(R^n|\alpha'\varepsilon_t)^{\frac{1}{2}}}$
A: $P_0, Y_0, M2_0 \leqq 0$; $RF_0 \geqq 0$

Table 3: Measuring Conditional Fit: (SZ prior, ET in differences)
Monetary System: $y_t = (Y_t, P_t, M2_t, RF_t, R_t^n, R_t^1)$

$\mathbf{R}^n$	$C^R\alpha$	**RMPD(b.p.)**			**RV(%)**			$\frac{\sigma_P}{\sigma_A}$		
		Pt. Est.	Pdf		Pt. Est.	Pdf		Pt.Est	Pdf	
2 mo	A	0.08	25%	0.111	9.707	25%	24.087	0.997	5%	0.869
			50%	0.146		50%	53.541		50%	1.863
			75%	0.186		75%	82.249		95%	4.123
3 mo	A	0.13	25%	0.192	8.240	25%	4.985	1.135	5%	0.886
			50%	0.253		50%	10.604		50%	1.01
			75%	0.328		75%	23.031		95%	1.274
4 mo	A	0.19	25%	0.210	1.645	25%	2.897	1.006	5%	0.902
			50%	0.277		50%	6.216		50%	1.007
			75%	0.360		75%	14.823		95%	1.191
6 mo	A	0.23	25%	0.233	1.350	25%	1.767	1.005	5%	0.928
			50%	0.312		50%	4.137		50%	1.005
			75%	0.408		75%	9.652		95%	1.128
9 mo	A	0.25	25%	0.246	0.775	25%	1.046	1.005	5%	0.945
			50%	0.334		50%	2.346		50%	1.004
			75%	0.440		75%	5.773		95%	1.091
12 mo	A	0.26	25%	0.244	0.637	25%	0.890	1.006	5%	0.952
			50%	0.336		50%	1.873		50%	1.003
			75%	0.447		75%	4.647		95%	1.083
24 mo	A	0.19	25%	0.243	0.210	25%	0.343	1.002	5%	0.961
			50%	0.331		50%	0.902		50%	1.002
			75%	0.445		75%	2.629		95%	1.067
36 mo	A	0.15	25%	0.228	0.084	25%	0.217	1.001	5%	0.969
			50%	0.310		50%	0.577		50%	1.001
			75%	0.417		75%	1.801		95%	1.046
48 mo	A	0.12	25%	0.216	0.038	25%	0.162	1.000	5%	0.973
			50%	0.295		50%	0.426		50%	1.001
			75%	0.392		75%	1.309		95%	1.036
60 mo	A	0.11	25%	0.204	0.028	25%	0.127	0.999	5%	0.974
			50%	0.278		50%	0.333		50%	1.000
			75%	0.370		75%	1.042		95%	1.034
120 mo	A	0.09	25%	0.175	0.022	25%	0.069	0.999	5%	0.978
			50%	0.234		50%	0.189		50%	1.000
			75%	0.308		75%	0.613		95%	1.026

* From simulated posterior distribution based on 1000 draws

RMPD $= [\frac{1}{48}\sum_{t=0}^{47}[S_t^{n,1} - \frac{1}{k}\sum_{j=1}^{k-1}(R_{t+j}^1 - R_t^1)]^2]^{\frac{1}{2}}$

RV. $= \frac{var(premium|\alpha'\varepsilon_t)}{var(S_{t_t}^{n,1}|\alpha'\varepsilon_t)} * 100\%$

$\frac{\sigma_P}{\sigma_A} = \frac{var(\frac{1}{k}\sum_{j=1}^{k-1}(R_{t+j}^1 - R_t^{f1})|\alpha'\varepsilon_t)^{\frac{1}{2}}}{var(S_t^{n,1}|\alpha'\varepsilon_t)^{\frac{1}{2}}}$

A: $Y_0, P_0, M2_0 \leqq 0$; $RF_0 \geqq 0$;

Table 4
Measuring Conditional Fit (Money Demand Shock)
Monetary System: $y_t = (Y_t, P_t, M2_t, RF_t, R_t^n, R_t^1)$

$\mathbf{R}^n$	$C^R\alpha$	**RMPD**	**Relative Var.**	$\frac{\sigma_P}{\sigma_A}$
2 mo	A	0.25	0.55%	2.094
3 mo	A	0.40	1.80%	1.381
4 mo	A	0.53	3.48%	0.929
6 mo	A	0.75	15.05%	2.090
9 mo	B	0.83	19.50%	2.977
12 mo	B	0.88	24.76%	3.408
24 mo	B	0.84	27.09%	4.484
36 mo	C	0.82	17.62%	3.953
48 mo	C	0.78	26.12%	5.178
60 mo	C	0.74	36.45%	6.398
120 mo	C	0.49	46.37%	9.901

A: $\mathrm{Y}_0 \leqq 0; P_0 \leqq 0; M2_0 \geqq 0; RF_0 \geqq 0; RF_3 \geqq 0; Y_{24} \leqq P_{24}; P_3 \leqq P_0; M2_0 \geqq -P_0; P_{36} \leqq 0$
B: $\mathrm{Y}_0 \leqq 0; P_0 \leqq 0; M2_0 \geqq 0; RF_0 \geqq 0; RF_3 \geqq 0; Y_{24} \leqq P_{24};\ P_3 \leqq P_0$
C: $\mathrm{Y}_0 \leqq 0; P_0 \leqq 0; M2_0 \geqq 0; RF_0 \geqq 0; RF_3 \geqq 0; Y_{24} \leqq P_{24}$

Table 5
Contemporaneous Structure of the Benchmark Model ($R^n = R^{36}$)
With Maximum Likelihood Estimates

Money Demand:

$$\underset{(50.48,397.85)}{254.11}\ M2 + \underset{(107.93,189.57)}{171.01}\ RF - \underset{(-35.23,-11.90)}{26.55}\ Y - \underset{(-40.8245,9.16)}{17.62}\ P = \varepsilon_{MD}$$

Monetary Policy:

$$\underset{(-448.90,-227.85)}{-381.84}\ M2 + \underset{(2.49,157.59)}{90.61}\ RF = \varepsilon_{MP}$$

Financial Sector:

$$-\underset{(-60.47,-16.69)}{38.06}\ M2 - \underset{(-117.07,-97.32)}{107.08}\ RF - \underset{(-17.88,3.76)}{6.81}\ Y - \underset{(-63.81,-16.69)}{39.43}\ P +$$
$$\underset{(182.53,195.25)}{188.89}\ R^1 = \varepsilon_{R^1}$$

$$-\underset{(-47.19,-2.93)}{24.80}\ M2 - \underset{(-25.27,-4.34)}{14.68}\ RF - \underset{(-39.03,-17.38)}{27.80}\ Y - \underset{(-78.27,-31.53)}{54.34}\ P -$$
$$\underset{(-113.93,-94.74)}{103.99}\ R^1 + \underset{(271.55,290.43)}{281.21}\ R^{36} = \varepsilon_{R^{36}}$$

68% equal tailed probability intervals based on 50,000 draws from the posterior distribution of model coefficients in parentheses.

Table 6
Incorporating Policy Responses to the Bond Market:
Implications for the Conditional Expectations Theory
(5%,16%,84%,95%) fractiles

	Benchmark		$\mu_{R^n} = .05$		$\mu_{R^n} = .25$	
R^n	**RMPD**	**Rel. Var.**	**RMPD**	**RV**	**RMPD**	**RV**
2mo	0.29 (0.93,1.29,3.02,3.08)	.22% (.22%,.66%,11.91%,23.48%)	0.28	.20%	0.24	.16%
3mo	0.82 (0.93,1.29,3.02,3.76)	1.91% (.25%,.76%,13.28%,26.17%)	0.79	1.81%	0.63	1.39%
4mo	1.15 (0.93,1.03,3.04,3.76)	3.54% (.26%,.92%,13.80%,26.28%)	1.10	3.40%	1.10	3.40%
6mo	1.60 (0.90,1.26,3.00,3.77)	5.69% (.36%,.83%,12.20%,23.70%)	1.51	5.44%	1.19	4.37%
9mo	2.03 (0.84,1.16,2.80,3.60)	8.49% (.33%,.87%,11.54%,24.18%)	1.90	7.95%	1.42	5.79%
1yr	2.26 (0.85,1.18,2.84,3.65)	11.45% (.47%,1.05%,12.01%,26.36%)	2.08	10.49%	1.43	6.67%
2yr	2.50 (1.05,1.51,4.10.5.36)	37.24% (1.15%,2.76%,32.93%,74.61%)	2.27	34.56%	1.35*	21.30%
3yr	2.57 (1.14,1.70,4.99,6.60)	48.64% (1.59%,4.25%,59.99%,132.73%)	2.34	46.11%	1.30*	30.97%
4yr	2.53 (1.27,1.90,5.71,7.56)	51.31% (2.51%,6.14%,90.47%,139.61%)	2.28	48.41%	1.23**	31.48%
5yr	2.38 (1.35,2.06,6.21,8.21)	45.75% (2.88%,7.05%,121.70%,160.13%)	2.12	42.24%	1.09**	23.33%
10yr	1.78 (1.62,2.46,7.31,9.71)	32.54% (4.52%,12.05%,150.58%,150.58%)	1.48	26.73%	0.49**	5.61%

RMPD $= [\frac{1}{48}\sum_{t=0}^{47}(R_t^n - \frac{1}{n}\sum_{j=0}^{n-1} R_{t+j}^1)^2]^{\frac{1}{2}}$
Relative Var.(RV) $= \frac{var(premium|\varepsilon_{MP})}{var(R^n|\varepsilon_{MP})} * 100\%$
* Outside 68% interval
** Outside 90% interval

____
Fractiles based on 50,000 draws from the posterior
distribution for RMPD and Rel. Variance statistics in parentheses.

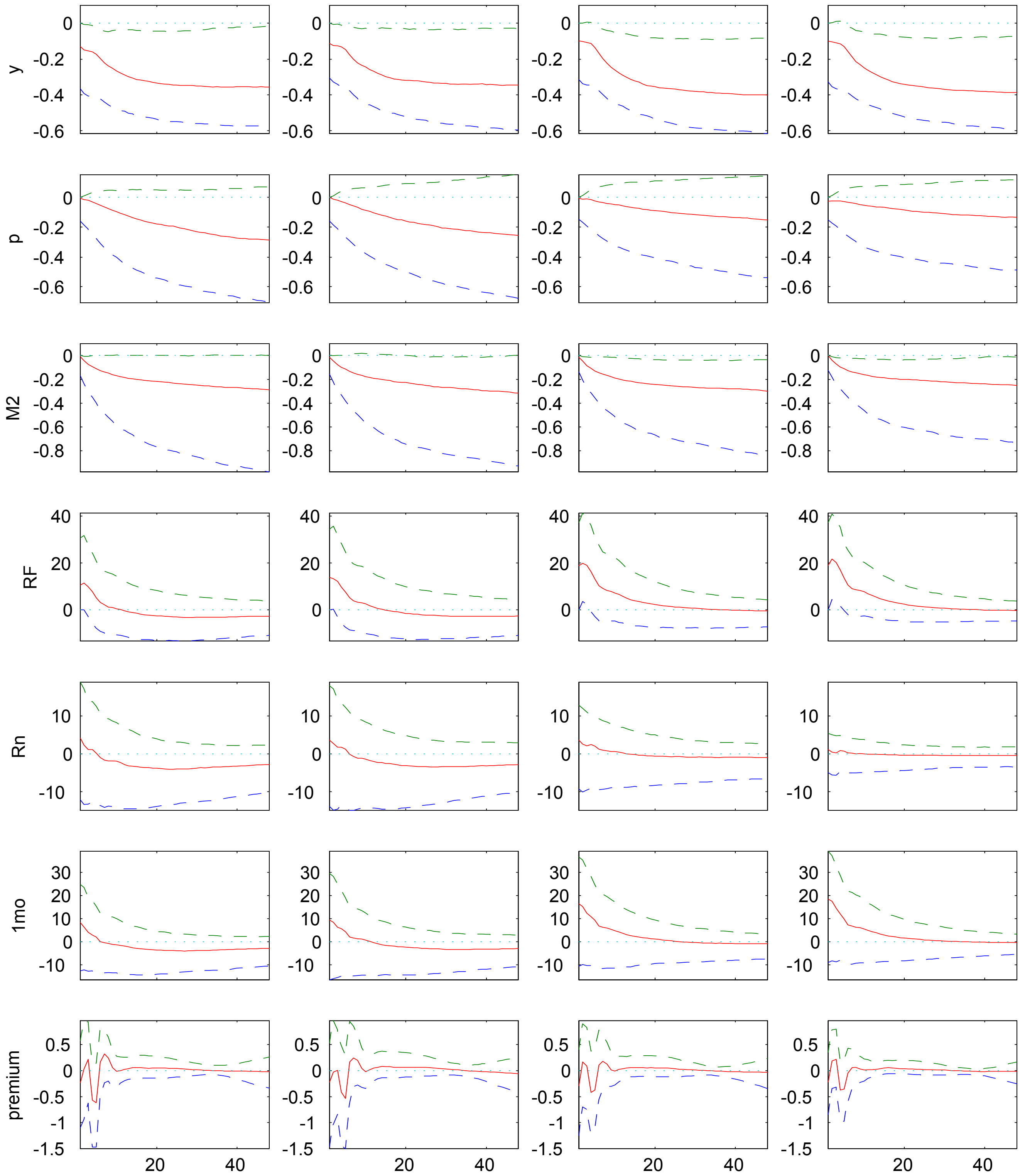


Figure 1: Impulse Responses to a Policy Shock (Rn: n=6, 12, 36 ,120 months) (SZ Prior; ET in Levels)

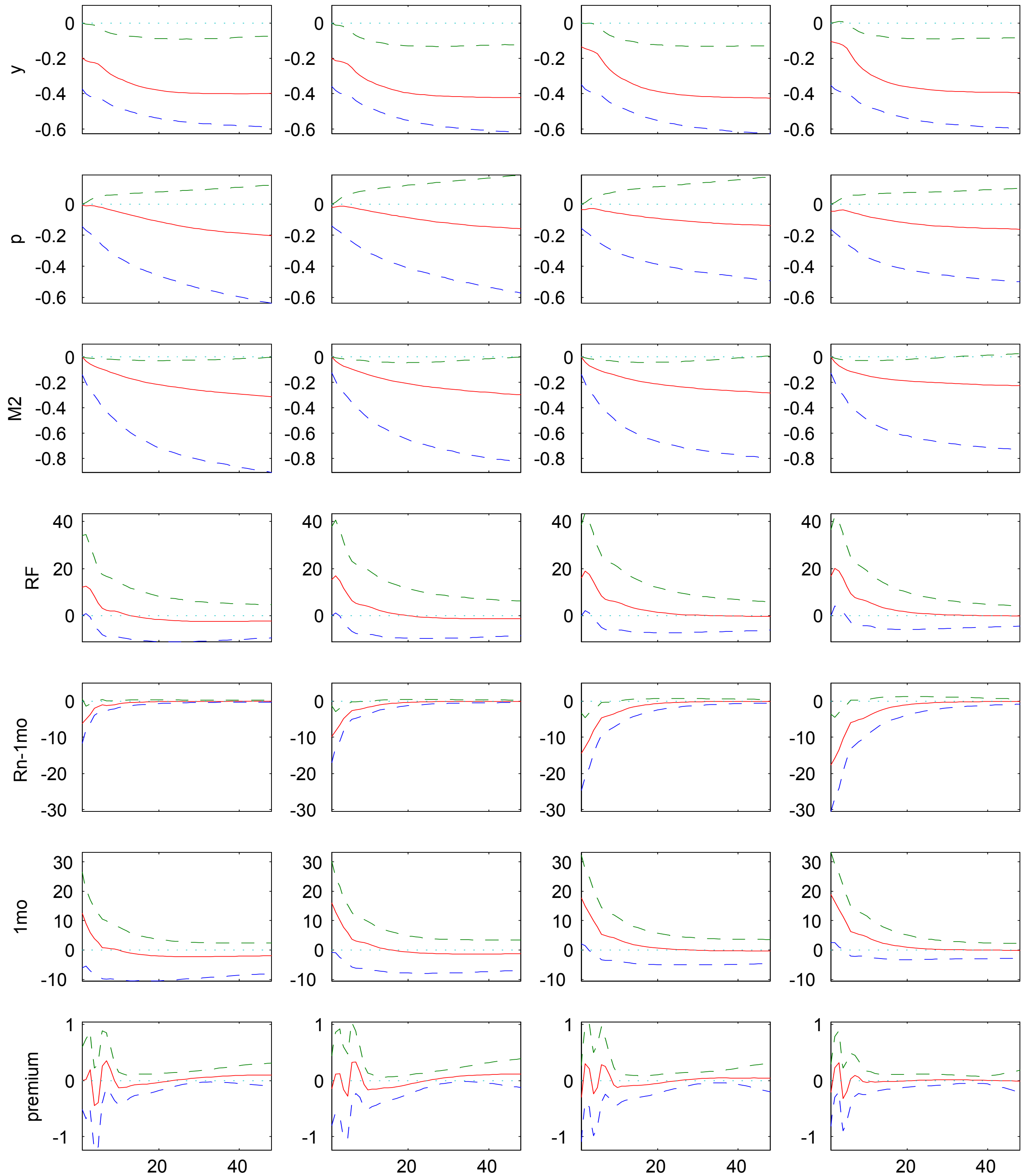


Figure 2: Impulse Responses to a Policy Shock: (Rn: n= 6, 12 36, 120 months) (SZ prior; ET in Spreads)

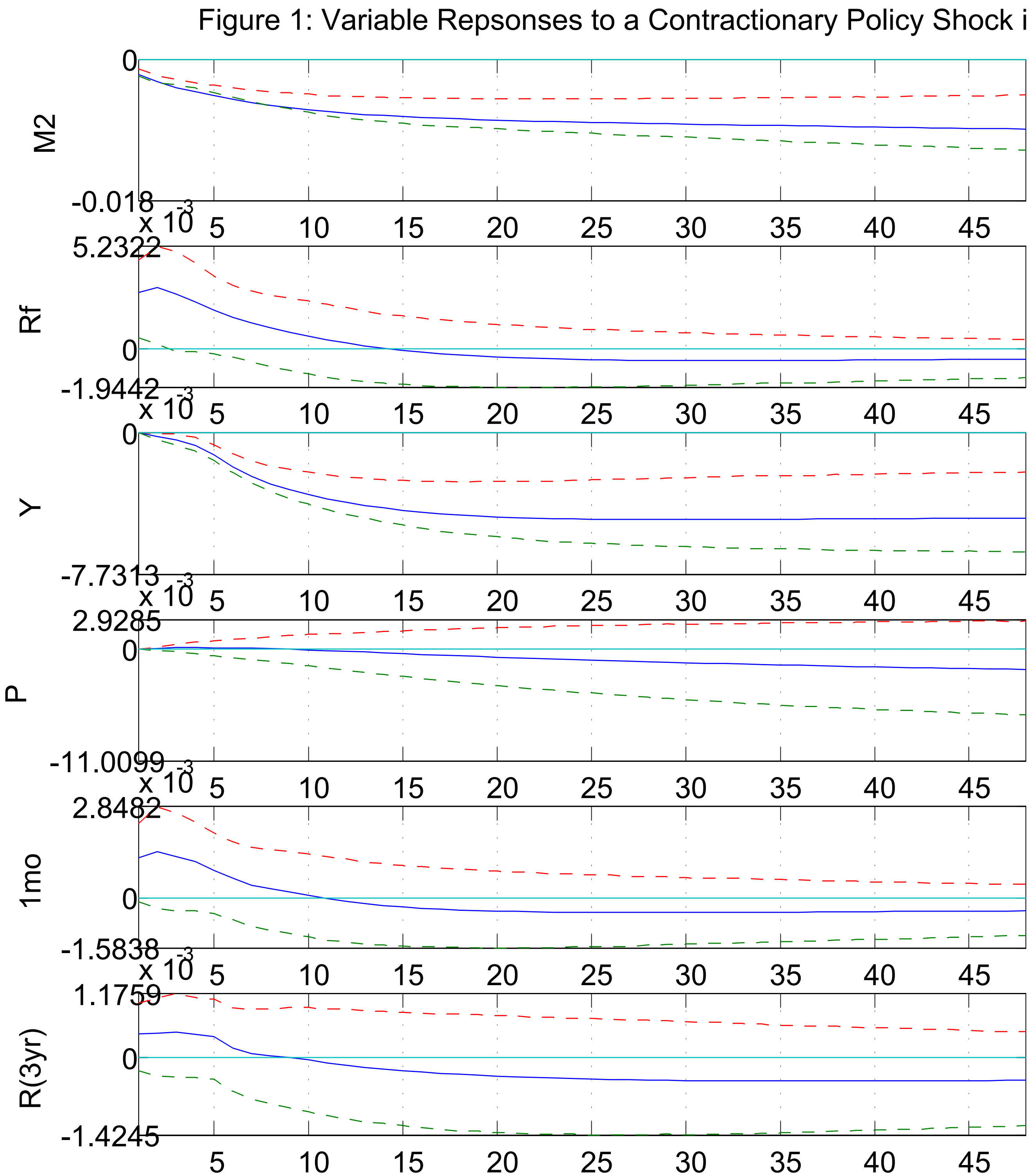


Figure 1: Variable Repsonses to a Contractionary Policy Shock i
M2
0
-0.018
x 10^-3
5.2322
Rf
0
-1.9442
x 10^-3
0
Y
-7.7313
x 10^-3
2.9285
0
P
-11.0099
x 10^-3
2.8482
1mo
0
-1.5838
x 10^-3
1.1759
R(3yr)
0
-1.4245
5
10
15
20
25
30
35
40
45

Figure 3

Appendix A: Error Bands in Faust Proceedure

We obtain a sequence of 1000 draws from a posterior distribution of the reduced form VAR parameters, $B(L)$, formed with either the Sims Zha(1998), prior, or in the cases without a prior in the appendix, a flat prior. In the examples with a flat prior, this process is analogous to the RATS proceedure for exactly identified models. We describe implementation of the Sims Zha prior separately in appendix 5.

For each draw from the posterior distribution, we obtain the variance covariance matrix of one-step-ahead forecast errors and form a generic moving average representation, $C(L)\varepsilon_t = B(L)^{-1}HH^{-1}\mu_t$ using a Cholesky decomposition as described in section 2.1. We then perform the minimization problem described in equations 2.5 to 2.7 on each generic moving average representations, holding fixed the restrictions in $C^R\alpha \geq 0$.

Appendix B: Data

1. (Y): log of real GDP, seasonally adjusted, billions of chain 1992 dollars. Source: BEA. Monthly real GDP is interpolated by Leeper, Sims, Zha (1996)

2. (P) : log of CPI, consumer price index for urban consumers, seasonally adjusted. Source: Bureau of Economic Analysis, the Department of Commerce. (BEA)

3. (CP): log of Commodity prices, International Monetary Fund's index of world commodity prices. Source: International Financial Statistics

4. (TR) : log of total reserves stock, break adjusted, seasonally adjusted. Source: Board of Governors of the Federal Reserve System (BOG)

5. (RF) Federal funds effective rate, monthly average. Source: BOG; Continuously compounded and converted to 365 day basis.

6. ($M2$) : log of M2 money stock, seasonally adjusted, billions of dollars. Source: BOG

7. (R^n) : Long-Term Interest Rates, zero coupon bond yields, continuously compounded. 1959:1-1991:2 data are from the McColluch and Kwon data set that are also tax adjusted, 1992:2-1995:12 are from Bliss (1994) and are not tax adjusted. Evans and Marshall(1998) check the overlap in the data sets and find the difference in tax treatment in the two sets to be negligible.

Appendix C: The Sims Zha Prior (1998) and Implementation of the Soft Zero Restricitons

The Sims Zha(1998) joint normal prior for the parameters in $A(L)$ is constructed, for computational reasons, from a marginal distribution for A_0 and a conditional distribution for $\mathrm{A}_s|A_0, s > 0$. In sections 2.1 - 3, $A_0 = H$,a Cholesky decomposition of Σ_μ, while in section 4 A_0 is defined in Table 5.The marginal distribution for A_0 is initially specified with a diagonal covariance matrix on the non-zero elements of A_0. The conditional prior mean for $\mathrm{A}_1|A_0$ is A_0 itself while the conditional prior means for $\mathrm{A}_s|A_0, s > 0$, are zero reflecting an assumption that the reduced form models for individual variables are random walks. The prior standard deviations for the elements of A_s are assumed to shrink with s and the elements of A_s are also initially taken to be uncorrelated. Dummy observations are then added to the estimation in order to allow for correlation across the elements of A, reflecting an assumption that the processes are co-integrated which is helpful in correcting for the otherwise common occurrence in these models that the deterministic components of the estimated system explain an implausibly large amount of the historical variation in the data. The posterior distributions are simulated using the Gibbs sampling method for structural VARs developed in Waggoner and Zha(2000).

The imposition of zero restrictions on parameters in A_0 (as defined in table 5) is equivalent to imposing a degenerate prior distribution centered at zero on these paramenters. The soft zero restrictions implemented in section 4 relax this assumption by assuming that there is positive probablity of a non-zero parameter value– the prior distribution is now defined to have positive variance around a zero prior mean. Thus the larger the prior variance, the larger the assumed probability that the parameter will deviate from zero. To implement the non-zero prior assumptions in the alternative policy specifications in the paper, we set the prior variance on the long rate parameter in the policy equation equal to a fraction $\mu \in [0,1]$ of the prior variance of the other contemporaneous parameters. Thus a higher value of μ reflects a larger prior variance on R^n in the policy equation and a smaller degree of assymetry across the prior variance assumptions for the elements of A_0.

Appendix D: Alternative Specifications

Model A

Measuring Conditional Fit: (Flat Prior, ET in levels)

Monetary System: $y_t = (Y_t, P_t, M2_t, RF_t, R_t^n, R_t^1)$

$\mathbf{R}^n$	$C^R\alpha$	**RMPD(b.p.)**			**RV(%)**			$\frac{\sigma_A}{\sigma_P}$	
		Pt. Est.	Pdf		Pt. Est.	Pdf		Pt. Est.	Pdf
			25%*	0.85		25%*	0.60		5%*
2 mo	A	0.89	50%	1.01	1.14	50%	1.14		50%
			75%	1.45		75%	1.95		95%
			25%	1.32		25%	1.12		5%
3 mo	A	1.11	50%	1.56	1.15	50%	2.17		50%
			75%	2.68		75%	3.78		95%
			25%	1.14		25%	0.99		5%
4 mo	A	1.16	50%	1.42	1.53	50%	2.09		50%
			75%	1.73		75%	4.19		95%
			25%	1.21		25%	1.30		5%
6 mo	B	1.30	50%	1.60	1.43	50%	2.52		50%
			75%	1.98		75%	5.12		95%
			25%	1.32		25%	1.69		5%
9 mo	C	1.37	50%	1.73	1.55	50%	3.13		50%
			75%	2.19		75%	6.65		95%
			25%	1.09		25%	1.39		5%
12 mo	D	1.20	50%	1.43	1.61	50%	2.79		50%
			75%	1.89		75%	6.07		95%
			25%	1.00		25%	1.68		5%
24 mo	D	0.95	50%	1.33	1.53	50%	4.61		50%
			75%	1.77		75%	15.59		95%
			25%	0.85		25%	1.79		5%
36 mo	E	0.68	50%	1.13	1.28	50%	5.08		50%
			75%	1.58		75%	17.64		95%
			25%	0.75		25%	1.80		5%
48 mo	F	0.63	50%	0.99	1.19	50%	4.75		50%
			75%	1.22		75%	15.74		95%
			25%	0.78		25%	1.84		5%
60 mo	G	0.61	50%	0.99	1.07	50%	5.68		50%
			75%	1.25		75%	23.18		95%
			25%	0.67		25%	2.78		5%
120 mo	H	0.59	50%	0.83	3.71	50%	9.14		50%
			75%	1.07		75%	31.71		95%

RMPD $= [\frac{1}{48}\sum_{t=0}^{47}(R_t^n - \frac{1}{k}\sum_{j=0}^{k-1} R_{t+j}^1)^2]^{\frac{1}{2}}$;RV. $= \frac{var(premium|\alpha'\varepsilon_t)}{var(R^n|\varepsilon_{MP})} * 100\%$; $\frac{\sigma_P}{\sigma_A} = \frac{var(\frac{1}{k}\sum_{j=1}^{k-1} R_{t+j}^1|\alpha'\varepsilon_t)^{\frac{1}{2}}}{var(R^n|\alpha'\varepsilon_t)^{\frac{1}{2}}}$

Restricitions for Model A:

A : $P_0, Y_0, M2_0 \leqq 0$; $RF_0 \geqq 0$; $.75RF_1 \leqq R_0^1 \leqq 1.25RF_1$; $Y_0 \geqq .5M2_0; P_0 \geqq .5M2_0; P_6 \leqq 0$; $RF_0 \geqq -265M2_0$

B : A except $Rf_0 \geqq -125M2_0$; C : B except $Rf_0 \geqq -110M2_0$

D : $P_0, Y_0, M2_0 \leqq 0; RF_0 \geqq 0; Y_0 \geqq .5M2_0, .95RF_1 \leqq R_0^1 \leqq 1.05RF_1; Y_1 \leqq Y_0$;

E : D except$.85RF_1 \leqq R_0^1 \leqq 1.15$;

F : E except $.95RF_1 \leqq R_0^1 \leqq 1.05RF_1$ and $M2_0 \geqq 4Y_0$;

G : F exceptModel A $M2_0 \geqq 2Y_0$; H : G except $.98RF_1 \leqq R_0^1 \leqq 1.02RF_1$

Model A:
Contemporaneous Policy Parameter Estimates

Monetary System: $y_t = (Y_t, P_t, M2_t, RF_t, R_t^n, 1mo_t)$

R^n	**Y**	**P**	**M2**	**RF**	**R^n**	**1mo**
2mo	-39.47	-86.43	-231.98	1.39	-3.72	3.73
3mo	-25.52	-37.26	-212.89	1.47	-3.19	2.79
4mo	-24.59	-39.08	-233.85	1.40	-2.69	2.31
6mo	-38.49	-0.60	-402.21	0.87	-1.46	1.32
9mo	-41.36	-1.03	-425.13	0.72	-1.05	0.95
12mo	-41.32	-9.66	-433.33	0.47	-0.95	1.04
24mo	-35.67	-10.52	-418.32	0.28	-1.10	1.12
36mo	-22.48	-15.06	-444.49	0.03	-0.88	1.09
48mo	-14.55	-7.95	-448.92	0.06	-0.92	1.01
60mo	-37.85	-12.77	-431.41	0.04	-0.93	1.05
120mo	-48.08	-180.23	-346.81	0.05	-0.69	1.19

Model B

Measuring Conditional Fit: (SZ prior, ET in levels)

Monetary System: $y_t = (Y_t, P_t, M2_t, RF_t, R_t^n, R_t^1)$

$\mathbf{R}^n$	$C^R\alpha$	**RMPD(b.p.)**			**RV(%)**			$\frac{\sigma_P}{\sigma_A}$		
		Pt. Est.	Pdf		Pt. Est.	Pdf		Pt.Est	Pdf	
			25%	0.19		25%	0.037		5%	0.9723
2 mo	A	0.18	50%	0.24	2.188	50%	0.102	0.8992	50%	0.9992
			75%	0.31		75%	0.322		95%	1.0079
			25%	0.24		25%	0.057		5%	0.9686
3 mo	A	0.29	50%	0.31	0.149	50%	0.160	0.9966	50%	0.9990
			75%	0.40		75%	0.494		95%	1.0076
			25%	0.25		25%	0.069		5%	0.9604
4 mo	A	0.30	50%	0.32	0.103	50%	0.198	0.9999	50%	0.9987
			75%	0.43		75%	0.595		95%	1.0073
			25%	0.27		25%	0.093		5%	0.9460
6 mo	A	0.19	50%	0.37	0.037	50%	0.264	0.9997	50%	0.9980
			75%	0.50		75%	0.810		95%	1.0057
			25%	0.29		25%	0.106		5%	0.9547
9 mo	A	0.17	50%	0.40	0.114	50%	0.292	0.9991	50%	0.9977
			75%	0.56		75%	0.779		95%	1.0035
			25%	0.28		25%	0.101		5%	0.9465
12 mo	A	0.26	50%	0.39	0.086	50%	0.280	0.9997	50%	0.9978
			75%	0.58		75%	0.959		95%	1.0035
			25%	0.27		25%	0.150		5%	0.9199
24 mo	A	0.32	50%	0.39	0.147	50%	0.401	0.9995	50%	0.9975
			75%	0.52		75%	0.145		95%	1.0028
			25%	0.25		25%	0.169		5%	0.8938
36 mo	A	0.29	50%	0.35	0.139	50%	0.463	0.9998	50%	0.9972
			75%	0.48		75%	1.863		95%	1.0020
			25%	0.24		25%	0.175		5%	0.8572
48 mo	A	0.26	50%	0.33	0.127	50%	0.591	.09998	50%	0.9966
			75%	0.46		75%	2.287		95%	1.0014
			25%	0.23		25%	0.197		5%	0.8690
60 mo	A	0.23	50%	0.32	0.135	50%	0.715	0.9997	50%	0.9961
			75%	0.44		75%	2.882		95%	1.0009
			25%	0.19		25%	0.302		5%	0.7851
120 mo	A	0.15	50%	0.26	0.159	50%	1.422	0.9995	50%	0.9928
			75%	0.35		75%	5.529		95%	1.0002

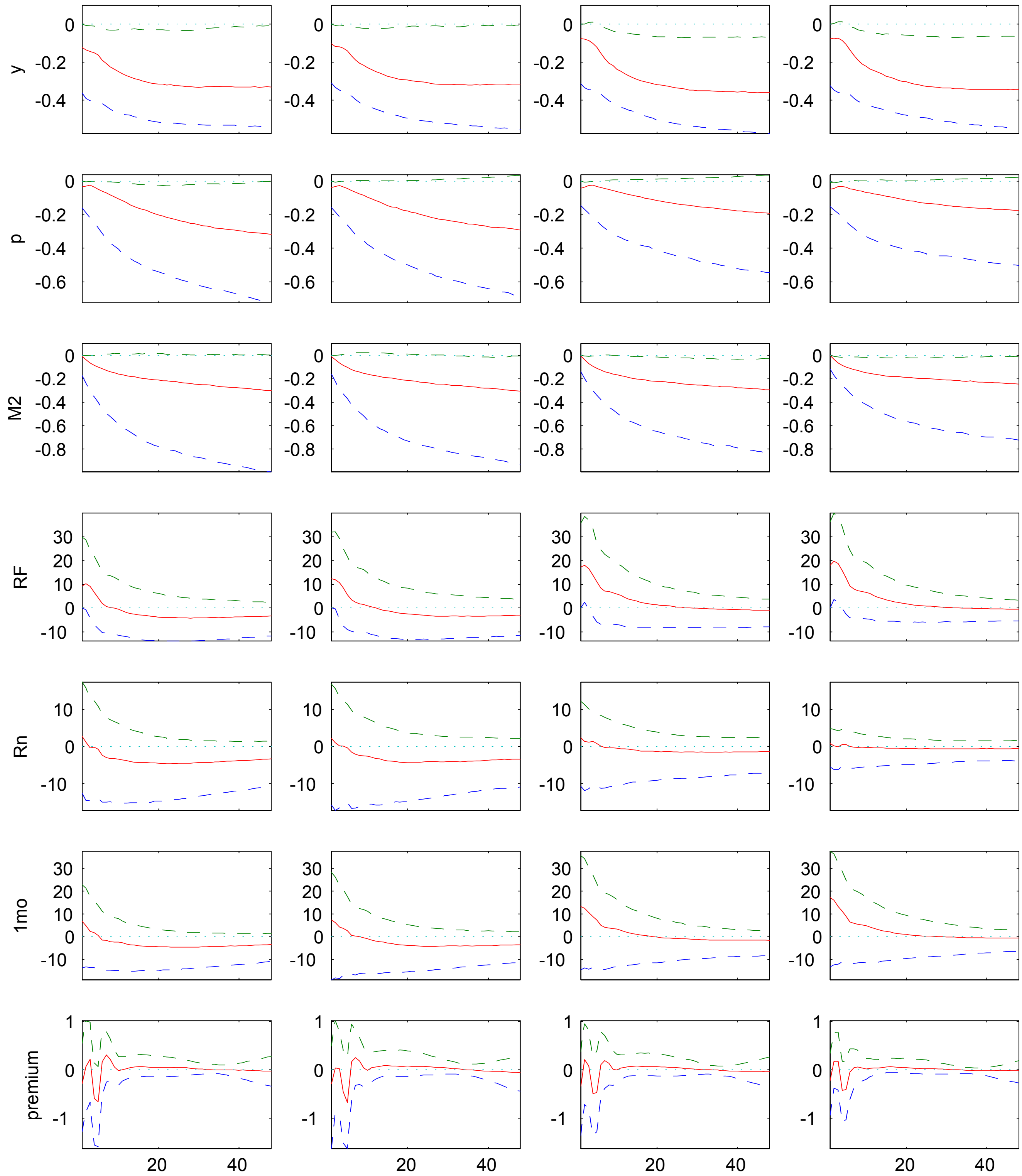
* From simulated posterior distribution based on 1000 draws

RMPD $= [\frac{1}{48}\sum_{t=0}^{47}[S_t^{n,f} - \frac{1}{k}\sum_{j=1}^{k-1}(R_{t+j}^f - R_t^f)]^2]^{\frac{1}{2}}$

RV. $= \frac{var(premium|\alpha'\varepsilon_t)}{var(S_t^{n,f}|\alpha'\varepsilon_t)} * 100\%$

$\frac{\sigma_P}{\sigma_A} = \frac{var(\frac{1}{k}\sum_{j=1}^{k-1}(Rf - R_t^f)|\alpha'\varepsilon_t)^{\frac{1}{2}}}{var(S_t^{n,1})|\alpha'\varepsilon_t)^{\frac{1}{2}}}$

$A : P_0 = Y_0 = 0; PC_0, M2_0, TR_0 \leqq 0; RF_0 \geqq 0; P_3 \leq 0$



Impulse Responses to a Policy Shock: Model B

Model C :

Measuring Conditional Fit: (SZ prior, ET in differences)

Monetary System: $y_t = (Y_t, P_t, PC_t, TR_t, RF_t, M2_t, R_t^n)$

$\mathbf{R}^n$	$C^R\alpha$	**RMPD(b.p.)**			**RV(%)**			$\frac{\sigma_P}{\sigma_A}$		
		Pt. Est.	Pdf		Pt. Est.	Pdf		Pt.Est	Pdf	
2 mo	A	0.75	25%	0.448	27.034	25%	6.092	0.3091	5%	0.1446
			50%	0.618		50%	14.311		50%	0.3169
			75%	0.823		75%	46.167		95%	0.7832
3 mo	A	0.30	25%	0.251	9.675	25%	5.447	0.9661	5%	0.6776
			50%	0.334		50%	10.58		50%	0.9209
			75%	0.431		75%	19.56		95%	1.0271
4 mo	A	0.25	25%	0.224	1.38	25%	1.803	0.9827	5%	0.8371
			50%	0.295		50%	3.700		50%	0.9798
			75%	0.383		75%	7.462		95%	1.0444
6 mo	A	0.25	25%	0.216	0.97	25%	0.720	0.9900	5%	0.9254
			50%	0.294		50%	1.479		50%	0.9981
			75%	0.388		75%	3.158		95%	1.0399
9 mo	A	0.21	25%	0.221	0.37	25%	0.400	1.0011	5%	0.9528
			50%	0.299		50%	0.834		50%	1.0000
			75%	0.396		75%	1.766		95%	1.0355
12 mo	A	0.22	25%	0.226	0.266	25%	0.295	1.0029	5%	0.9643
			50%	0.302		50%	0.627		50%	1.0002
			75%	0.392		75%	1.344		95%	1.0284
24 mo	A	0.27	25%	0.231	0.154	25%	0.215	0.9997	5%	0.9662
			50%	0.304		50%	0.535		50%	1.0005
			75%	0.398		75%	1.404		95%	1.0400
36 mo	A	0.24	25%	0.222	0.091	25%	0.177	0.9996	5%	0.9686
			50%	0.296		50%	0.427		50%	1.0004
			75%	0.384		75%	1.278		95%	1.0408
48 mo	A	0.25	25%	0.216	0.072	25%	0.154	0.9996	5%	0.9703
			50%	0.289		50%	0.394		50%	1.0009
			75%	0.379		75%	1.144		95%	1.0484
60 mo	A	0.24	25%	0.207	0.262	25%	0.127	1.0001	5%	0.9761
			50%	0.281		50%	0.344		50%	1.0008
			75%	0.370		75%	1.021		95%	1.0495
120 mo	A	0.143	25%	0.182	0.089	25%	0.077	0.9999	5%	0.9813
			50%	0.245		50%	0.198		50%	1.0009
			75%	0.323		75%	0.666		95%	1.0389

* From simulated posterior distribution based on 1000 draws

RMPD $= [\frac{1}{48}\sum_{t=0}^{47}[S_t^{n,f} - \frac{1}{k}\sum_{j=1}^{k-1}(R_{t+j}^f - R_t^f)]^2]^{\frac{1}{2}}$

RV. $= \frac{var(premium|\alpha'\varepsilon_t)}{var(S_t^{n,f}|\alpha'\varepsilon_t)} * 100\%$

$\frac{\sigma_P}{\sigma_A} = \frac{var(\frac{1}{k}\sum_{j=1}^{k-1}(Rf - R_t^f)|\alpha'\varepsilon_t)^{\frac{1}{2}}}{var(S_t^{n,1})|\alpha'\varepsilon_t)^{\frac{1}{2}}}$

$A : P_0 = Y_0 = 0; PC_0, M2_0, TR_0 \leqq 0; RF_0 \geqq 0$

Model D

Measuring Conditional Fit: (no prior, ET in levels)

Monetary System: $y_t = (Y_t, P_t, PC_t, TR_t, RF_t, M2_t, R_t^n)$

$\mathbf{R}^n$	$C^R\alpha$	**RMPD(b.p.)**			**RV(%)**			$\frac{\sigma_P}{\sigma_A}$	
		Pt. Est.	Pdf		Pt. Est.	Pdf		Pt. Est.	Pdf
			25%*	1.1		25%*	2.1		5%*
2 mo	A	3.8	50%	1.4	6.1	50%	5.5		50%
			75%	3.9		75%	15.5		95%
			25%	1.4		25%	2.1		5%
3 mo	B	3.2	50%	2.4	3.9	50%	3.9		50%
			75%	3.3		75%	8.2		95%
			25%	1.2		25%	1.4		5%
4 mo	B	2.4	50%	1.8	2.2	50%	2.4		50%
			75%	1.5		75%	4.5		95%
			25%	1.1		25%	0.7		5%
6 mo	B	2.1	50%	2.0	1.8	50%	1.4		50%
			75%	3.3		75%	3.0		95%
			25%	1.6		25%	1.1		5%
9 mo	C	3.6	50%	2.8	5.6	50%	3.0		50%
			75%	4.2		75%	7.0		95%
			25%	1.6		25%	2.7		5%
12 mo	B	5.0	50%	2.8	11.8	50%	8.8		50%
			75%	4.2		75%	20.3		95%

* From simulated pdf based on 1000 draws

RMPD $= [\frac{1}{48}\sum_{t=0}^{47}(R_t^n - \frac{1}{k}\sum_{j=0}^{k-1} R_{t+j}^f)^2]^{\frac{1}{2}}$

RV $= \frac{var(premium|\alpha'\varepsilon_t)}{var(R^n|\alpha'\varepsilon_t)} * 100\%$

$\frac{\sigma_P}{\sigma_A} = \frac{var(\frac{1}{k}\sum_{j=1}^{k-1} R_{t+j}^f|\alpha'\varepsilon_t)^{\frac{1}{2}}}{var(R^n|\alpha'\varepsilon_t)^{\frac{1}{2}}}$

$A: P_0 = Y_0 = 0; PC_0, M2_0, TR_0 \leqq 0; RF_0 \geqq 0; Y_{60} \leqq 0;$
$P_2 \leqq -.025PC_2; M2_0 \geqq .15TR_{10}.$

$B: A$ except $M2_0 \geqq .10TR_{10}$

$C: B$ with $TR_0 \leqq .4Y_{12}$

Model E

Measuring Conditional Fit: (SZ prior, ET in levels)

Monetary System: $y_t = (Y_t, P_t, PC_t, TR_t, RF_t, M2_t, R_t^n)$

$\mathbf{R}^n$	$C^R\alpha$	**RMPD(b.p.)**			**RV(%)**			$\frac{\sigma_A}{\sigma_P}$		
		Pt. Est.	Pdf		Pt. Est.	Pdf		Pt.Est	Pdf	
			25%	0.272		25%	0.217		5%	0.9854
2 mo	A	0.27	50%	0.390	0.768	50%	0.637	1.0282	50%	1.0044
			75%	0.571		75%	2.064		95%	1.1054
			25%	0.25		25%	0.156		5%	0.9814
3 mo	A	0.22	50%	0.34	1.205	50%	0.491	1.0268	50%	1.0021
			75%	0.48		75%	1.290		95%	1.0623
			25%	0.22		25%	0.100		5%	0.9846
4 mo	A	0.19	50%	0.30	0.039	50%	0.264	1.0022	50%	1.0007
			75%	0.39		75%	0.807		95%	1.0348
			25%	0.21		25%	0.084		5%	0.9770
6 mo	A	0.15	50%	0.27	0.089	50%	0.256	0.9967	50%	0.9993
			75%	0.37		75%	0.711		95%	1.0170
			25%	0.22		25%	0.098		5%	0.9521
9 mo	A	0.20	50%	0.30	0.075	50%	0.283	0.9956	50%	0.9977
			75%	0.43		75%	0.839		95%	1.0064
			25%	0.23		25%	0.116		5%	0.9233
12 mo	A	0.34	50%	0.32	0.141	50%	0.367	0.9860	50%	0.9964
			75%	0.48		75%	1.177		95%	1.006
			25%	0.242		25%	0.195		5%	0.8619
24 mo	A	0.54	50%	0.358	0.365	50%	0.582	0.9877	50%	0.9948
			75%	0.508		75%	2.15		95%	1.0030
			25%	0.223		25%	0.243		5%	0.8368
36 mo	A	0.43	50%	0.329	0.447	50%	0.776	0.9880	50%	0.9933
			75%	0.485		75%	3.275		95%	1.0025
			25%	0.328		25%	0.298		5%	0.7902
48 mo	A	0.47	50%	0.476	0.806	50%	1.105	0.9851	50%	0.9920
			75%	0.857		75%	4.713		95%	1.0015
			25%	0.215		25%	0.337		5%	0.7324
60 mo	A	0.43	50%	0.316	15.276	50%	1.379	0.8680	50%	0.9911
			75%	0.458		75%	5.673		95%	1.0014
			25%	0.190		25%	0.399		5%	0.6488
120 mo	A	0.29	50%	0.269	45.99	50%	1.996	0.6116	50%	0.9881
			75%	0.370		75%	9.791		95%	1.0002

RMPD $= [\frac{1}{48}\sum_{t=0}^{47}[R_t^n - \frac{1}{k}\sum_{j=1}^{k-1} R_{t+j}^f)]^2]^{\frac{1}{2}}$

RV. $= \frac{var(premium|\alpha'\varepsilon_t)}{var(R^n|\alpha'\varepsilon_t)} * 100\%$

$\frac{\sigma_p}{\sigma_A} = \frac{var(\frac{1}{k}\sum_{j=1}^{k-1} R_{t+j}^f|\alpha'\varepsilon_t)^{\frac{1}{2}}}{var(R^n|\alpha'\varepsilon_t)^{\frac{1}{2}}}$

A: $P_0, Y_0, PC, TR_0, M2_0 \leqq 0$; $RF_0 \geqq 0$

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