US MONETARY POLICY & UNCERTAINTY: TESTING BRAINARD'S HYPOTHESIS

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Abstract. This paper presents an empirical analysis of the impact of time-varying economic uncertainty on US monetary policy activism. I use a latent factor based measure, extracted from a set of five different variables, to proxy economic uncertainty. Monetary policy activism is inferred from a time-varying Taylor Rule estimated using a structural VAR allowing for stochastic volatility. Contrary to Brainard's Principle, the results point to a substantial Hansen and Sargent type reaction: monetary policy activism increases significantly in response to an increase in economic uncertainty. The estimates, moreover, indicate that both inflation and unemployment activism respond roughly equally to changes in aggregate uncertainty.

1. Introduction

This paper studies the impact of time-varying economic uncertainty on US monetary policy activism. Since Brainard's [1967] seminal paper, economists have debated the normative impact of economic uncertainty on monetary policy. Broadly speaking, existing approaches can be classified into three categories: (1) Bayesian decision theoretical approaches (Brainard [1967] and Rudebusch [2001]); (2) robust min-max monetary policy rules (Hansen and Sargent [2007]); and (3), robust policy rules with structured uncertainty (Onatski and Stock [2000]). Despite similarities in the models analyzed, the three approaches often lead to contradicting policy implications. Models applying Bayesian approaches generally abide by the Brainard Principle, stating that policy should exhibit conservatism in the face of uncertainty (in the sense of having a smaller coefficient on the output gap and inflation in a Taylor Rule). Central bank "experimentation" can appear to lessen, although not invalidate, this effect (Wieland [1998, 2006]).[1] The Brainard Principle contrasts with the findings using robust min-max monetary policy rules where increases in economic uncertainty lead to more aggressive responses by the monetary authorities to minimize the worst-case risk (often called the Hansen and Sargent Principle). However, as shown by Onatski and Stock [2000], the finding that min-max policy

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[1]The Brainard Principle, as Wieland [1998, 2006] shows, tends to be attenuated in a framework including learning where uncertainty will also motivate an element of experimentation in policy. Despite this effect, the optimal policy that balances the cautionary and activist motives in these (Bayesian) models still exhibits gradualism; i.e. a less active policy when uncertainty increases. Gaspar et al. [2006] and Orphanides and Williams [2006] consider alternative aspects of central bank learning, achieving roughly similar results regarding the impact of uncertainty on monetary policy activism as Wieland [1998]. To some extent therefore, central bank experimentation can appear to diminish - but not invalidate - the distinction between the Brainard and the Hansen and Sargent Principles. Nevertheless, as Svensson and Williams [2007] show, the benefits from experimentation can for most classes of forward-looking models appear very modest and, in some specifications, even insignificant.

rules are more aggressive than standard linear-quadratic rules does not necessarily hold for all types of model perturbations.

In this paper, I provide the first, to my knowledge, empirical characterization of the impact of economic uncertainty on monetary policy activism. I estimate measures of US economic uncertainty and Federal Reserve activism, and use these to investigate whether the Brainard or the Hansen and Sargent Principle have been dominant in US monetary policy making.

I use five different proxies of economic uncertainty: (1) a measure of stock market volatility; (2) GARCH-implied aggregate growth volatility; (3) the cross-sectional interquartile range of industrial output growth; (4) the dispersion in professional forecasters one-year-ahead output forecasts; and finally (5), the dispersion in measures of business expectations from consumer and producer surveys. Rather than analyzing these separately - or selecting any single one of them, as the literature has done so far - I use the method proposed by Giannone et al. [2008] to separate the common factor, denoted economic uncertainty, from the idiosyncratic noise contained in each proxy. I find that economic uncertainty is highly countercyclical, responding to both global political and economic shocks. Uncertainty, for instance, spikes during the Vietnam War, the two OPEC crises and during the recent financial turmoil.

To estimate US monetary policy activism, I use a three-variable time-varying Bayesian VAR with Stochastic Volatility [TVC-BVAR with SV] comprised of inflation, unemployment and interest rates. I detect sizable and persistent variation in the responsiveness of the Federal Reserve. In particular, in response to an inflation shock, real interests rates appear to decrease during the chairmanship of Arthur F. Burns only to increase rapidly with the arrival of Paul A. Volcker. Since then, monetary policy has mostly abided by the Taylor Principle, although there appears to have been a large trend decrease in activism during the tenure of Alan Greenspan. Furthermore, the responsiveness of the Federal Reserve with regards to inflation and unemployment is highly correlated, indicating that periods of inflation activist policies coincide with periods of high responsiveness to measures of spare capacity.

I analyze the impact of the latent factor based measure of economic uncertainty on monetary policy activism using a simple linear GMM approach. As an instrument for economic uncertainty, I use lagged values: the latent factor based method employed to extract time-varying uncertainty implies that lagged values show a high-degree of correlation with contemporaneous. In my estimation, I control for changes in the chairmanship of the Board of Governors; changes in the formal policy framework; movements in financial (in)stability; and lastly, for large spikes in inflation and unemployment.

Contrary to Brainard's [1967] Principle, my estimates indicate a significant Hansen and Sargent type reaction. Long-run coefficients on inflation and unemployment in a Taylor Rule increase by in between 0.100 and 0.541 in response to a two standard deviation increase in economic uncertainty (roughly the increase in uncertainty witnessed during the recent crisis). Moreover, increases in uncertainty have a positive and statistically significant effect on inflation activism across all specifications. Unemployment activism similarly responds positively to economic uncertainty; however, the effect is across most regressions slightly smaller - although the difference is not statistically significant - and appears to depend relatively more on the exact measure of activism employed. Finally, this paper also shows that the results presented appear robust to the exact measure of policy activism used: comfortingly, most results also carry over to cases using real-time data on Federal Reserve expectations to estimate monetary policy activism.

1.1. **Related Literature.** This work is linked to three strands of literature. First, this paper is related to the literature estimating the direct impact of stock market implied uncertainty on monetary policy. Bekaert et al. [2010] and Rigobon and Sack [2003] find that monetary authorities react to periods of high uncertainty by easing policy rates. However, both authors employ a time-invariant framework and their results are therefore confounded by the possibility that monetary policy *activism* might respond to economic uncertainty.

Second, this paper complements the recent empirical literature examining the impact of economic uncertainty on real output. Bloom [2009] and Bekaert et al. [2010] use implied stock market volatility as a proxy of economic uncertainty, whereas Alexopoulos and Cohen [2009], Bachmann et al. [2010] and Popescu and Smets [2010] use a newspaper citation based measure, the dispersion in business expectations derived from business surveys and the disagreement in professional forecasters one-year ahead output forecasts as their proxies of economic uncertainty, respectively. The impact of innovations to economic uncertainty on aggregate activity found appears to depend crucially on the exact proxy of uncertainty used. For instance, Popescu and Smets [2010] and Bachmann et al. [2010] find much smaller effects of economic uncertainty on industrial production than originally found by Bloom [2009]. In addition, they find no empirical support for theoretical "overshoot effects" (Bloom [2009] and Bloom et al. [2010]), whereby innovations to economic uncertainty cause a subsequent output overshoot as the increased volatility of business conditions triggers a medium-term hiring boom. Arguably, the latent factor based measure employed in this paper should provide a cleaner estimate of economic uncertainty by disentangling the noise from the signal in the proxies. For instance, stock market volatility, the proxy used by Bloom [2009], is also impacted by changes in risk-appetite, which economic impact might differ significantly from that of aggregate uncertainty.

Finally, this paper is related to the vast literature estimating time-varying monetary policy reaction functions to debate whether the cause of the poor economic performance of the 1970s and early 1980s was due to "bad monetary policy" or just "bad luck" (i.e. a sequence of adverse shocks). Important references are DeLong [1997], Bernanke and Mihov [1998], Clarida et al. [2000], Orphanides [2001], Sims [2001], Cogley and Sargent [2005], Primiceri [2005] and Boivin [2006]. Recently, estimated DSGE models as in Gambetti et al. [2008] and Fernández-Villaverde et al. [2010] have also been employed to investigate these issues. On aggregate, the recent literature appears to favor the "bad luck" explanation, although sizable variation in the parameters of estimated Taylor Rules, consistent with large changes in the conduct of monetary policy from the mid 1970s to the early 1980s, are also found.

In this paper, I follow the procedure of Primiceri [2005] and Cogley and Sargent [2005] and use a TVC-BVAR with SV, approximating a small structural model, to estimate a time-varying Taylor Rule for the US Federal Reserve. The literature, highlighted above, has however considered alternative approaches. Broadly speaking, these can be classified into three categories: (1) estimated DSGE models using time-varying Bayesian VARs as in Gambetti et al. [2008] and Fernández-Villaverde et al. [2010]; (2) time-varying coefficient Bayesian VARs *without* stochastic volatility as in Cogley and Sargent [2001]; and finally (3), direct estimation of time-varying Taylor Rules using Kalman Filter techniques and either ML or QLR-estimation as in Kim and Nelson [2006] and Boivin [2006].

On the methodological side, estimated DSGE models have the advantage of using theoretically derived identifying restrictions. That said, stochastic volatility has until recently not been included in these models (see Fernández-Villaverde et al. [2010]). Nonetheless, as this paper shows - and as originally argued by Sims' [2001] review of Cogley and Sargent [2001] - stochastic volatility appears important in explaining the innovations impacting the aggregate economy. In addition, the estimated DSGE model in Fernández-Villaverde et al. [2010], allowing for stochastic volatility, uses relatively tight priors to obtain results, rather than the uninformative data driven priors used in this paper. The Kalman Filter techniques suggested by Kim and Nelson [2006] and Boivin [2006] have the advantage of being computationally easier to implement. However, they rely on either ML-estimation - and are therefore subject to the 'Pile-up Problem' (Harvey et al. [1994]), whereby the ML estimator of the covariance matrix has a point mass at zero - or on a fixed (small) number of breaks in the standard deviation of the shocks. As this paper shows, there appears to be rather many persistent changes in the standard deviation of innovations to the Taylor Rule, and the changes do not appear to be confined to a single period. Furthermore, any type of learning dynamics will also favor a model with drifting coefficients over one with discrete breaks.

1.2. **Organization.** The rest of the paper is organized as follows. The next section presents the latent factor based measure of economic uncertainty, while Section 3 estimates monetary policy activism using a TVC-BVAR with SV. Section 4 presents and discusses the GMM estimates of the impact of time-varying aggregate uncertainty on US monetary policy activism. Section 5 concludes.

2. Measuring Economic Uncertainty[2]

In this section, I present a new measure of US aggregate economic uncertainty and analyze how it compares to other, previously suggested, proxy measures. Given that economic uncertainty is fundamentally unobservable, I rely on the common factor extracted from a set of proxy measures consisting of five variables - one of which I suggest as a new proxy of economic uncertainty. Clearly, such an approach remains filled with difficulties in the absence of a direct reliable measure. Nevertheless, the combined use of several proxies and the associated disentangling of the noise from the signal should improve on previous estimates and generate a more dependable benchmark from which to assess the impact of economic uncertainty on monetary policy activism.

2.1. **Data.** The complete set of proxy variables used in the estimation are: (1) a measure of stock market volatility; (2) GARCH-implied aggregate growth volatility; (3) the cross-sectional interquartile range of industrial output growth; (4) the dispersion in professional forecasters one-year ahead output forecasts[3]; and finally (5), the dispersion in measures of business expectations from consumer and producer surveys (details can be found in Appendix A). The list of proxy measures considered includes all but one previously analyzed variable used in the literature, as well as one new measure: the dispersion in consumer business surveys.[4]

[2]This section borrows heavily from Kohlhas [2011].

[3]An alternative - and perhaps theoretically more appealing - measure of professional forecaster dispersion would be the variance of a combined density forecast. However, there are two reasons for why the more 'standard' measure employed in this paper is preferable. First, the Survey of Professional Forecasters by the Philadelphia Federal Reserve only provides combined density forecasts on a consistent basis going back to 1992Q1. Second, some doubts about the validity of the stated individual density forecasts have been cast in the literature, see e.g. Diebold et al. [1997].

[4]Alexopoulos and Cohen [2009] are currently updating their newspaper based measure to include more journals. Therefore, it is not included in this analysis.

2.2. **Econometric Method.** In order to efficiently estimate the common factor on the unbalanced data set comprised by the five monthly proxies of macroeconomic uncertainty, I use a framework that closely follows that of Giannone et al. [2008] and Banbura and Modugno [2010] with only minor differences with regards to the initialization of the procedure. The main advantage of this framework is that it efficiently handles a relatively small cross-section (allowing for missing observations) by utilizing both cross-sectional and time variation in generating the estimates of the underlying factors. As the method is 'non-standard', I briefly outline it below.

Let $\mathbf{y}_t = [y_{1t}, y_{2t}, ..., y_{nt}]'$, $t = 1, ..., T$ denote a stationary n-dimensional vector process. Throughout the analysis, I assume that $\mathbf{z_t}$ - the standardized version of $\mathbf{y_t}$ - admits the following dynamic factor model representation:

$$\mathbf{z_t} = \mathbf{\Lambda F_t} + \epsilon_\mathbf{t}, \quad \epsilon_\mathbf{t} \sim WN(\mathbf{0}, \mathbf{\Psi}) \tag{2.1}$$

$$\mathbf{F_t} = \mathbf{\Phi_1 F_{t-1}} + ... + \mathbf{\Phi_p F_{t-p}} + \eta_\mathbf{t}, \quad \eta_\mathbf{t} \sim WN(\mathbf{0}, \mathbf{\Sigma}), \tag{2.2}$$

where $\mathbf{F_t}$ is an $r \times 1$ vector of (unobserved) common factors, $\mathbf{\Lambda} = [\lambda_\mathbf{1}, ..., \lambda_\mathbf{n}]'$ is an $n \times r$ matrix of factor loadings and $\epsilon_\mathbf{t} = [\epsilon_{1t}, \epsilon_{2t}, ..., \epsilon_{nt}]'$ is the idiosyncratic error term with: $\mathbb{E}[\epsilon_\mathbf{t}\epsilon_\mathbf{t}'] = diag(\psi_1, ..., \psi_n) = \mathbf{\Psi}$, $\mathbb{E}[\epsilon_\mathbf{t}\epsilon_\mathbf{s}'] = \mathbf{0}$, $\forall s \neq t$ and uncorrelated with $\mathbf{F_t}$ at all leads and lags, $\mathbb{E}[\epsilon_\mathbf{t}\eta_\mathbf{s}'] = \mathbf{0}$, $\forall s$ (i.e., I assume an exact factor model structure).

An initial estimate of the common factors is found using iterative least squares:[5]

$$\left(\left\{\hat{\mathbf{F}}_\mathbf{t}\right\}_{t=1}^{t=T}, \hat{\mathbf{\Lambda}}\right) = \underset{\{\mathbf{F_t}\}_{t=0}^{t=T}, \mathbf{\Lambda}}{\arg\min} \left\{\sum_{t=1}^{T}\sum_{i=1}^{n}\left(z_{it} - \lambda_\mathbf{i}'\mathbf{F_t}\right)^2\right\}. \tag{2.3}$$

The unbalanced panel nature of our dataset is accommodated by summing over non-missing observations.[6] Once (2.3) is solved, $\mathbf{\Psi}$ can be estimated as $\hat{\mathbf{\Psi}} = 1/(T-1)\sum_{t=1}^{T}\hat{\epsilon}_\mathbf{t}\hat{\epsilon}_\mathbf{t}'$ and the remaining parameters can be estimated by running a VAR on the estimated factors:

$$\begin{aligned} \hat{\mathbf{\Phi}}' &= \sum_{t=p+1}^{T}\hat{\mathbf{F}}_\mathbf{t}\mathbf{x}_\mathbf{t}'\left(\sum_{t=p+1}^{T}\mathbf{x_t}\mathbf{x}_\mathbf{t}'\right)^{-1} \\ \hat{\mathbf{\Sigma}} &= \frac{1}{T-p-1}\sum_{t=p+1}^{T}\hat{\eta}_\mathbf{t}\hat{\eta}_\mathbf{t}', \end{aligned} \tag{2.4}$$

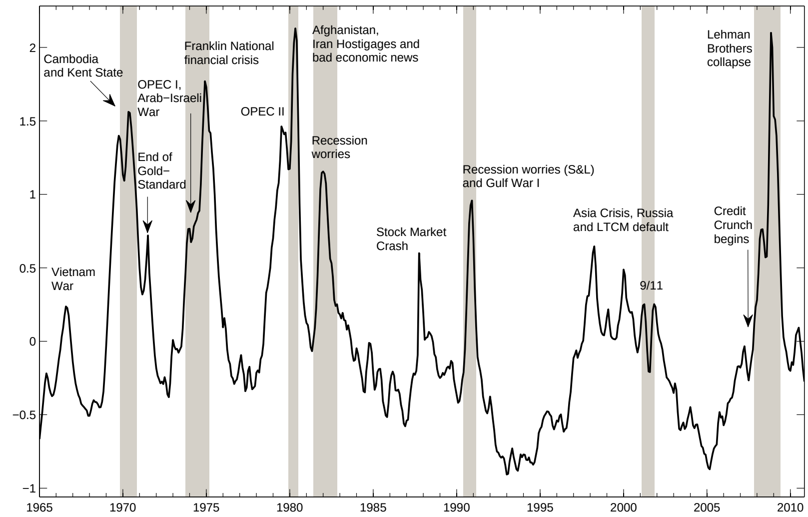
where $\mathbf{x}_\mathbf{t}' = \left[\hat{\mathbf{F}}_\mathbf{t-1}', \hat{\mathbf{F}}_\mathbf{t-2}', \ldots, \hat{\mathbf{F}}_\mathbf{t-p}'\right]$ and $\mathbf{\Phi}' = \left[\mathbf{\Phi_1}, \mathbf{\Phi_2}, \ldots, \mathbf{\Phi_p}\right]$.

The estimated parameters, $\hat{\mathbf{F}}_\mathbf{t}$, $\hat{\mathbf{\Lambda}}$, $\hat{\mathbf{\Psi}}$, $\hat{\mathbf{\Phi}}$ and $\hat{\mathbf{\Sigma}}$ now fully populate the state space given by equations (2.1) and (2.2). An improved estimate of $\mathbf{F_t}$, which now invokes time-series averaging, can therefore be computed using the Kalman

[5] This is where I differ from Giannone et al. [2008]. As some of the proxy measures are only available for a very short period of time, principal components - the procedure normally used to obtain initial estimates of the common factors - would be estimated on very few observations.

[6] When the panel is balanced, the solution to the least squares problem provides the principal components of z_{it}, which can also be estimated as the eigenvectors of the sample covariance matrix. However, in this unbalanced panel data set an iterative two-step procedure has to be implemented to solve the least squares problem. Estimation is carried out when I have data on three or more uncertainty proxies. I use 500 iterations and 25 different starting values. That said, in all cases the procedure converged after roughly 100 iterations. As $\mathbf{\Lambda F_t} = \mathbf{\Lambda Q Q^{-1} F_t}$ for any non-singular matrix $\mathbf{Q}$, only the column space of the factors can be identified. The common factor is therefore normalized to have identity second moment matrix. See also Hatzius et al. [2010].

Figure 2.1. US Macroeconomic Uncertainty



US Macroeconomic Uncertainty. Shaded areas correspond to NBER Recession dates.

Smoother.[7] That said, the Kalman Smoother does not exploit any time series or cross-sectional correlation (possibly) present in the error terms, which are treated as uncorrelated both in time and in cross-section. But, as first proved by Doz et al. [2007], consistent estimates of the common factors still hold under an 'approximate factor structure'.[8]

2.3. **US Macroeconomic Uncertainty.** The latent factor measure of economic uncertainty, unc_t, is estimated from January 1965 to October 2010, corresponding to the subsample for which I have at least three uncertainty proxies. Throughout the analysis, I assume a lag length of two, $p = 2$ (experimenting with higher order lags resulted in similar estimates), and the existence of only one common factor, $r = 1$. From a theoretical perspective all the measures were chosen to proxy the same underlying variable: macroeconomic uncertainty. Therefore, one should a priori expect there to be only one common factor. Correspondingly, the first common factor explains over 61% of the overall variation, with the other factors contributing at most 14%. Figure 2.1 depicts the uncertainty measure.

As we can see, uncertainty appears to dramatically increase following major economic and political shocks like the Vietnam War, the end of the Gold Standard and the two OPEC crises. The wide variety of shocks causing spikes in uncertainty is also apparent, ranging from domestic terrorist attacks to financial market crises in developing economies. Furthermore, uncertainty is highly countercyclical, often doubling during stages of economic downturns. In fact, not only does the latent factor measure exhibit this feature, but *all* of the uncertainty proxies show

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[7]Notice that the parameters $\hat{\mathbf{\Lambda}}$, $\hat{\mathbf{\Psi}}$, $\hat{\mathbf{A}}$ and $\hat{\mathbf{\Sigma}}$ could be re-estimated using the new factors $\hat{\mathbf{F}}_t$ from the Kalman Smoother. This is the first step of the EM algorithm proposed by Banbura and Modugno [2010]. By iterating until convergence, one obtains ML estimates under gaussianity. That said, I re-estimated the latent factor model on the unbalanced data set using this approach, but found only very modest changes compared to the two-step procedure.

[8]An alternative to using Iterative Least Squares coupled with the Kalman Smoother to extract the common factor is Bayesian Shrinkage techniques, see Mol et al. [2008]. That said, the results I obtained using Bayesian Shrinkage as well as standard Principal Components appear very similar.

Table 1. Factor Loadings

λ_i'	(1)	(2)	(3)	(4)	(5.1)	(5.2)
Unc	0.91	0.74	1.01	1.13	0.99	0.43
R^2	$0.59^{\dagger}$	0.23	0.45	0.54	0.56	0.17

Variable numbers are put in parentheses: (1) measure of stock market volatility; (2) GARCH-implied aggregate growth volatility; (3) the cross-sectional range of industrial production growth; (4) the dispersion in professional forecasters one-year ahead output forecasts; and finally (5), the dispersion in measures of business expectations from consumer (5.1) and producer surveys (5.2) [see also Appendix A]. All coefficients are significant at the 5% level. † indicates a variable where the 1987 stock market crash has been excluded in the calculation of R^2.

rapid increases during recessions. It is therefore a consistent finding that the distribution of agents perceptions of the macroeconomy shifts during downturns: the mean-outcome worsens and the variance increases. In a recent paper, Mele [2009] summarizes theoretical reasons for why uncertainty might be counter-cyclical. The most important appear to be: (1) incomplete information about non-linearities in the economy, (2) non-convex adjustment costs, as also highlighted by Bloom [2009], and (3), the procyclicality of financial market risk-taking. Finally, a noticeable feature of Figure 2.1 is the Great Moderation. The volatility of uncertainty apparently decreased markedly in the 1990s and early 2000s with spikes only registering at half the levels seen in previous decades.

To assess which uncertainty proxies load most heavily onto the economic uncertainty measure, Table 1 presents the factor loadings, λ_i', and the associated R^2. As Table 1 shows, the uncertainty measure explains a large proportion of the variation in the financial market based proxy of economic uncertainty as well as the measures of forecast dispersion and consumer expectations. That said, for each proxy there remains a large part of the total variation which is attributed to proxy-specific noise, unrelated to economic uncertainty. As argued, this was to be expected, caused by, for instance, risk-aversion also partially driving stock market volatility. The disentangling of this noise from the signal is a clear advantage of the latent factor based uncertainty measure.

Interestingly, the latent factor explains very little of the variation in the business expectations category, (5.2), which is identical to the measure used by Bachmann et al. [2010]. This could suggest that part of the reason for why their results differ meaningfully from the rest of the literature on the impact of uncertainty shocks is that the measure of uncertainty they employ is fairly uncorrelated with the other proxy measures. The difference between the proportion explained by the common factor of the consumer and business expectation categories is also striking. Part of this difference might be explained by the group of firms sampled being subject to industry and region specific shocks, whereas the consumer category assesses aggregate economic expectations. That said, the difference among the survey based categories is puzzling.

3. Monetary Policy Activism

In this section, I estimate US monetary policy activism using a time-varying Bayesian VAR [TVC-BVAR] with stochastic volatility [SV]. I allow for drifting coefficients to capture changes in policy activism, but also to account for any non-linearities or changes in the lag structure present over the sample period. Multivariate stochastic volatility is included to allow for the variation in aggregate economic uncertainty documented in Section 2. In addition, as originally noted by Sims [2001], ignoring heteroskedasticity in the errors could vastly exaggerate the dynamics in the random coefficients. Allowing for both time variation in the coefficients and in the shocks leaves it up to the data to determine whether the fluctuations in the linear model are best derived from changing responses to homoskedastic shocks or from changes in the covariance matrix of the innovations. The procedure used follows that of Primiceri [2005] and Cogley and Sargent [2005].

Consider a modified version of the monetary policy rule in Clarida et al [2000]:

$$i_t = \rho(L)i_{t-1} + [1-\rho(L)]\, i_t^* + e_t^{MP} \tag{3.1}$$

$$i_t^* = i^* + \phi(L)\,[\pi_t - \pi^*] + \psi(L)\,[u_t - u^*]\,, \tag{3.2}$$

where i_t denotes the policy rate; i_t^* the "desired" policy rate; e_t^{MP}a monetary policy shock; π_t the inflation rate; π_t^* the target inflation rate; u_t the unemployment rate[9]; u_t^* the NAIRU; and i^*, the equilibrium nominal interest rate. Finally, $\phi(L)$, $\psi(L)$ and $\rho(L)$ are lag polynomials. Equations (3.1) and (3.2) specify that the monetary authorities set the target interest rate, i_t^*, as a function of the inflation and unemployment gap; however, they only attain the target rate gradually as they smooth the transition from one target rate to the next. Combining the two equations gives:

$$i_t = \tilde{i}^* + \rho(L)i_{t-1} + \tilde{\phi}(L)\,[\pi_t - \pi^*] + \tilde{\psi}(L)\,[u_t - u^*] + e_t^{MP}, \tag{3.3}$$

where $\tilde{i}^* \equiv [1-\rho(1)]\, i^*$, $\tilde{\phi}(L) \equiv [1-\rho(L)]\,\phi(L)$ and $\tilde{\psi}(L) \equiv [1-\rho(L)]\,\psi(L)$. Equation (3.3) can be interpreted as a Taylor Rule, augmented to include higher-order dynamics.

Following Cogley and Sargent [2005], I define monetary policy activism with regards to inflation (α^π) and unemployment (α^u) as the long-run response of i_t to π_t and u_t, respectively:

$$\alpha^\pi \equiv \tfrac{\tilde{\phi}(1)}{1-\rho(1)} \tag{3.4}$$

$$\alpha^u \equiv \tfrac{\tilde{\psi}(1)}{1-\rho(1)}. \tag{3.5}$$

The policy rule is said to be "inflation activist" iff. $\alpha^\pi \geq 1$. In some models, an inflation activist monetary policy rule delivers a determinant equilibrium that eradicates sunspots as determinants of inflation and unemployment.[10]

As with most of the literature on *time-varying* Taylor Rules (see e.g. Villaverde et al [2010]), equation (3.3) includes contemporaneous and lagged explanatory variables. The extent to which policy makers also respond to expectations of future values of inflation and unemployment may therefore be thought to partially contaminate the findings. However, equation (3.3) can be re-interpreted as the reduced form of a forward-looking Taylor Rule, where expectations of future values of inflation and spare capacity depend upon current and lagged values of inflation, unemployment and interest rates through, as in this case, a VAR. In fact, Cogley and Sargent [2001] employ an analogous structural form using, like in this paper, a three-variable BVAR in their estimation of a time-varying Taylor Rule.

Alternatives to structural estimation of a forward-looking Taylor Rule exist. Most notably, Generalized Method of Moments [GMM] estimators assuming rational expectations, using contemporaneous and lagged variables as instruments, have been heavily popularized since Clarida et al [2001]. However, as shown by Mavroeidis [2005], drawing upon arguments made by Pesaran [1981], these estimators are highly unreliable as they are not empirically identified. Moreover, allowing for the

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[9]For comparison reasons, I focus on the unemployment rate, rather than a more traditional output gap based measure.

[10]This terminology follows Leeper [1991], who defined a monetary policy rule as active iff. the real interest rate increases in response to a permanent rise in inflation. See also Woodford [2003] for more on the link between model determinacy and activism.

possibility of dynamic misspecification, the identification becomes spurious, implying a highly significant coefficient on the forward-looking component irrespective of the true data generating process. As argued by Mavroeidis [2005], structural approaches to the estimation of forward-looking Taylor Rules therefore appear superior.

Explicitly modelling the expectation process of the Board of Governors of the Federal Reserve as depending only on a subset of variables may, however, be viewed as only approximating the true data generating process. I therefore, in Appendix B, investigate the robustness of the estimates of monetary policy activism using a simple forward-looking Taylor Rule estimated using real-time data on expectations. As an exogenous proxy of the Board of Governors' expectation of future inflation and spare capacity, I use the forecasts computed by the Staff of the Federal Reserve, published a few days before the FOMC meeting, and collected with a five year lag in what is known as the "Greenbook". There are, however, several important short-comings of this approach. First, there exists only a limited sample of relevant data. One year ahead forecasts are only consistently available from January 1974 to January 2005. Second, and perhaps more worrying, very little is known of the conditioning scenarios behind the Greenbook forecasts (Reifschneider, Stockton and Wilcox [1997]); in particular, what is assumed for the path of future policy rates. This could potentially imply some degree of endogeneity between the monetary policy shock, e_t^{MP}, and the expectation of, for instance, future inflation, $\mathbb{E}_t\left(\pi_{t+h}-\pi^*\right)$.[11] That said, for the overlapping sample, the estimation of a simple forward-looking Taylor Rule using Greenbook forecasts should provide a suitable robustness check of the results presented below.

3.1. **Model.** In order to estimate (3.3), allowing for time variation in α_t^{π} and α_t^{u} as well as simultaneity between π_t, u_t and i_t, I use a TVC-VAR with SV on $\mathbf{y_t}=[\pi_t,\, u_t,\, i_t]'$. Consider the model:

$$\mathbf{y_t}=\mathbf{c_t}+\mathbf{A_{1,t}}\mathbf{y_{t-1}}+\mathbf{A_{2,t}}\mathbf{y_{t-2}}+\ldots+\mathbf{A_{p,t}}\mathbf{y_{t-p}}+\epsilon_\mathbf{t},\quad \mathbb{V}[\epsilon_\mathbf{t}]=\mathbf{\Omega_t} \tag{3.6}$$

where $\mathbf{c_t}$ denotes a time varying $n\times 1$ vector of coefficients multiplying the constant term[12]; $\mathbf{A_{i,t}}$, $i=1,\ldots,p$, an $n\times n$ matrix of time-varying coefficients; and $\mathbf{e_t}$, an $n\times 1$ vector of heteroskedastic shocks with covariance matrix $\mathbf{\Omega_t}$.[13] Without loss of generality, consider the triangle reduction of $\mathbf{\Omega_t}$:

$$\mathbf{A_{0,t}}\mathbf{\Omega_t}\mathbf{A_{0,t}}'=\mathbf{H_t}\mathbf{H_t}', \tag{3.7}$$

where

$$\mathbf{A_{0,t}}=\begin{bmatrix}1&0&0\\a_{1t}&1&0\\a_{2t}&a_{3t}&1\end{bmatrix},\quad \mathbf{H_t}=\begin{bmatrix}h_{1t}&0&0\\0&h_{2t}&0\\0&0&h_{3t}\end{bmatrix}.$$

[11] If for instance the forecasts, as is the case for the Swedish Riksbank, are conditioned on market expectation of future interest rates, and those expectations are correct, endogeneity between the monetary policy shock and the measure of expectations would occur. For more on the Greenbook forecasts, see Appendix B.

[12] Note that the time varying constant accommodates, to a certain extent, misspecifications in the measure of spare capacity and/or changes in the inflation target.

[13] Small scale VARs, like the one considered in this paper, are common in the literature estimating monetary policy reaction functions, see e.g. Rotemberg and Woodford [1997] and Cogley and Sargent [2001]. n is in our case equal to 3; however, the model can be extended to any $n\epsilon\mathbb{N}_+$.

The assumption that $\mathbf{A_{0,t}}$ is lower-diagonal is not an identification assumption - although I will later use it to obtain the structural form - rather it is merely a particular way of parameterizing the reduced form covariance matrix.[14] The triangular reduction used in (3.7) is common in the VAR literature allowing separately for stochastic volatility and time-varying instantaneous coefficients, see e.g. Koop and Korobilis [2009]. Vectorizing the RHS coefficients in (3.6) and stacking them in $\mathbf{A_t}$ allows us to write the VAR in the SURE form as:

$$
\begin{aligned}
\mathbf{y_t} &= \mathbf{X_t'A_t} + \mathbf{A_{0,t}^{-1}H_te_t}, \quad V[\mathbf{e_t}] = \mathbf{I_n} \\
\mathbf{X_t'} &= \left[\mathbf{I_n} \otimes \left(1,\, \mathbf{y_{t-1}'},\, \mathbf{y_{t-2}'}, \ldots,\, \mathbf{y_{t-p}'}\right)\right].
\end{aligned} \tag{3.8}
$$

The approach taken is to model the parameters of (3.8) instead of (3.6). Specifically, the dynamics of the model parameters: $\mathbf{a_t} = [a_{1t},\, a_{2t},\, a_{3t}]'$, $\mathbf{A_t}$ and $\log(\mathbf{h_t}) = \log[h_{1t},\, h_{2t},\, h_{3t}]'$ are assumed to follow driftless random walks, i.e.

$$\mathbf{a_t} = \mathbf{a_{t-1}} + \mathbf{e_t^a} \tag{3.9}$$

$$\mathbf{A_t} = \mathbf{A_{t-1}} + \mathbf{e_t^A} \tag{3.10}$$

$$\log(\mathbf{h_t}) = \log(\mathbf{h_{t-1}}) + \mathbf{e_t^h}. \tag{3.11}$$

Modelling the diagonal components of $\mathbf{H_t}$ as geometric random walks implies that the model belongs to the class of VARs using stochastic volatility to capture heteroskedasticity in the errors. Alternative approaches are considered in Koop and Korobilis [2009]. As emphasized in Cogley and Sargent [2005], a random walk process hits any lower and upper bound with positive probability implying that the model might exhibit explosive behavior - a clearly undesirable property. That said, as long as the model is thought to be in place for a finite time period and not forever, this set of assumptions should be innocent enough (more on this later). In addition, the random walk assumptions greatly reduce the number of parameters in the estimation procedure and allow the parameters to exhibit numerous permanent shifts with the changes occurring over several periods. As demonstrated by Boivin [2006], the latter two features appear important in modelling monetary policy activism.

All the innovations in the model are assumed to be jointly normally distributed with covariance matrix given by:

$$
\mathbf{V} = \mathbb{V}\left(\begin{bmatrix} \mathbf{e_t} \\ \mathbf{e_t^a} \\ \mathbf{e_t^A} \\ \mathbf{e_t^h} \end{bmatrix}\right) = \begin{bmatrix} \mathbf{I_n} & 0 & 0 & 0 \\ 0 & \mathbf{V^a} & 0 & 0 \\ 0 & 0 & \mathbf{V^A} & 0 \\ 0 & 0 & 0 & \mathbf{V^h} \end{bmatrix}, \tag{3.12}
$$

where $\mathbf{V^i}$, $i = a,\, A,\, h$ is a symmetric positive definite matrix. In addition, I assume that $\mathbf{V^a}$ is block diagonal with blocks corresponding to parameters from different equations. The zero-blocks in $\mathbf{V}$ could be replaced with free parameters, as is for instance done in Koop et al [2009].[15] However, allowing for a complete covariance matrix would preclude any structural interpretation of the parameters. In addition,

[14] Primiceri [2005] discusses how, in theory, the choice of parametrization could affect the results. However, as shown by Koop et al [2009] empirically this does not seem relevant.

[15] Primiceri [2005] and Koop et al. [2009] report only very minor changes to their estimates when allowing for a full covariance structure in $\mathbf{V}$ instead of a block diagonal one.

the model is already heavily parametrized, so it is doubtful how much would be gained by including extra parameters.[16]

3.2. **Estimation Technique.** The estimation of (3.8) subject to (3.9)-(3.12) is done using Bayesian methods. The main advantage of this approach over classical estimation techniques is in dealing with the high dimensionality and non-linearity of the problem; the likelihood function most likely has several peaks, some of which will be in uninteresting regions of the parameter space not at all representative of the overall fit of the model. Bayesian methods can efficiently deal with this problem by using uninformative priors on "reasonable" areas of the parameter space. Furthermore, as shown by Harvey et al. [1994], the maximum likelihood estimator is subject to the so-called 'Pile-up Problem', implying that the ML estimator of the covariance matrix has a point mass at zero if the changes in the covariance terms are small. Besides, the maximization of a high-dimensional likelihood function is complicated and Monte Carlo Markov Chain [MCMC] methods provide an attractive alternative.

3.2.1. *Priors.* I follow the literature - in particular Cogley and Sargent [2005] and Primiceri [2005] - and use data driven normal-inverse-Wishart conjugate priors. The prior for $\mathbf{A^0}$ is chosen to be normal with mean equal to the LS point estimate on an initial subsample, $\mathbf{\hat{A}^{LS}}$, and variance equal to four times the variance of the time invariant VAR.[17] The prior for $\mathbf{a^0}$ is obtained in a similar way. For $\log(\mathbf{h^0})$, the mean of the distribution is chosen to be the logarithm of the LS point estimate while the covariance matrix is arbitrarily set equal to the identity matrix.[18]

The priors for the hyperparameters: $\mathbf{V^A}$, $\mathbf{V^h}$ and the blocks of $\mathbf{V^a}$ are assumed to be distributed as independent inverse-Wishart. In order to make the priors as diffuse as possible, the degrees of freedom are set to the smallest number possible to obtain a proper distribution (for instance, for $\mathbf{V^h}$, the degrees of freedom, $\underline{v}_h$, are set such that: $\underline{v}_h = dim(\mathbf{V^h}) + 1)$. That said, for $\mathbf{V^A}$ a slightly tighter prior was deemed necessary to avoid implausible behavior of the time-varying coefficients. The scale matrices, $\underline{\mathbf{Q}}_{\mathbf{A}}$, $\underline{\mathbf{Q}}_{\mathbf{h}}$ and $\underline{\mathbf{Q}}_{\mathbf{a},\mathbf{i}}$, $i = 1, \ldots S$, where S denotes the number of blocks in $\mathbf{V^a}$, are chosen to be constant fractions of the variances of the corresponding LS estimates on the initial subsample multiplied by the degrees of freedom (the reason being that for an inverse-Wishart distribution, the scale matrix can be interpreted as a residual sum of squared errors).

Succinctly, the priors can be written as:

---

[16]The total number of observations in this model is: $3T$. The number of parameters (incl. initial values) is equal to: 3 (initial parameters in $\mathbf{h}$) + 3 (initial parameters in $\mathbf{a}$) + $3(1 + 3p)$ (initial parameters in $\mathbf{A}$) + 6 (parameters in $\mathbf{V^h}$) + 3 (parameters in $\mathbf{V^a}$) + $3(1 + 3p)\,[3(1 + 3p) + 1]\,/2$ (parameters in $\mathbf{V^A}$) $= 3(1 + 3p)\left[\frac{3(1+3p)+1}{2} + 1\right] + 15$. Increasing the lag-length in this model therefore increases the parameter space quite rapidly. As discussed further below, there is therefore an added argument for keeping the lag-structure parsimonious.

[17]The history of a variable, $\mathbf{x_t}$, up until time T is denoted as: $\mathbf{x^T} = [\mathbf{x_1}, \mathbf{x_2}, \ldots, \mathbf{x_T}]$. Increasing the variance of the LS estimates by a factor of four is merely a way of guaranteeing that the priors are suitably uninformative.

[18]While the log-normal prior on $\boldsymbol{h^0}$ is standard in the stochastic volatility literature, see Primiceri [2005], it is technically not a conjugate prior. That said, the prior has the advantage of maintaining tractability.

$$\mathbf{A^0} \sim N\left(\mathbf{\hat{A}^{LS}},\, 4\mathbb{V}\left(\mathbf{\hat{A}^{LS}}\right)\right), \quad \mathbf{a^0} \sim N\left(\mathbf{\hat{a}^{LS}},\, 4\mathbb{V}\left(\mathbf{\hat{a}^{LS}}\right)\right)$$
$$\log\left(\mathbf{h^0}\right) \sim N\left(\log\left(\mathbf{\hat{h}^{LS}}\right),\, \mathbf{I_n}\right)$$
$$\mathbf{V^h} \sim IW\left(4k_h\mathbf{I_n},\, 4\right), \quad \mathbf{V^A} \sim IW\left(40k_A\mathbb{V}\left(\mathbf{\hat{A}^{LS}}\right),\, 40\right)$$
$$\mathbf{V_1^a} \sim IW\left(2k_a\mathbb{V}\left(\mathbf{\hat{a}_1^{LS}}\right),\, 2\right), \quad \mathbf{V_2^a} \sim IW\left(3k_a\mathbb{V}\left(\mathbf{\hat{a}_2^{LS}}\right),\, 3\right),$$

where $k_a = 0.1^2$ and $k_A = k_h = 0.01^2$ are set according to the literature while $\mathbf{V_1^a}$ and $\mathbf{V_2^a}$ specifies the two blocks of $\mathbf{V^a}$. The priors used are therefore not flat, but diffuse and uninformative, so that the data is free to speak about the relevant features.

3.2.2. *Simulation Method.* The model is estimated by simulating the distribution of the unknown parameters using MCMC methods. The Gibbs Sampler is used to exploit the block structure of the unknowns and draw a sample from the joint posterior, $p\left(\mathbf{a^T},\, \mathbf{A^T},\, \log(\mathbf{h^T}),\, \mathbf{V}\right)$, given the data. Gibbs Sampling procedes in four steps. First, I draw the time varying coefficients, $\mathbf{A^T}$, using the Carter and Kohn [1994] simulation smoother.[19] Second, conditional on $\mathbf{A^T}$, $\mathbf{a^T}$ is part of a normal linear state space and can therefore be sampled using the same method. Third, conditional on the first two parameters, drawing $\log(\mathbf{h^T})$ can be done using the method presented in Kim et al [1998]. And finally, fourth, simulating the conditional distribution of $\mathbf{V}$ is done in a standard way as it is a product of independent inverse-Wishart distributions. Details of the simulation method used can be found in Koop and Korobilis [2009] and Primiceri [2005].

3.3. **Identification.** The model described so far is a reduced form model. Identifying assumptions must be made to allow for a structural interpretation. I begin in a standard fashion by ordering the dependent variable, $\mathbf{y_t}$, as $\mathbf{y_t} = [\pi_t,\, u_t,\, i_t]'$. The structural model has the form

$$\mathbf{y_t} = \mathbf{X_t'A_t} + \mathbf{B_t u_t},$$

where $\mathbf{B_t}$ imposes the identifying assumptions and $\mathbf{u_t}$ denotes the structural innovations. The identifying assumption for the monetary policy shock is that changes in the policy rate have no immediate impact on inflation and unemployment. This identification assumption is standard in the literature, see e.g. Bernanke and Mihov [1998] and Christiano et al [1998]. Regarding the non-policy block, π_t and u_t, I assume that unemployment has no contemporaneous impact on inflation.[20] Combined, these assumptions imply that $\mathbf{B_t}$ is lower diagonal (given by a Cholesky decomposition) and can be found from the reduced form parameters as:

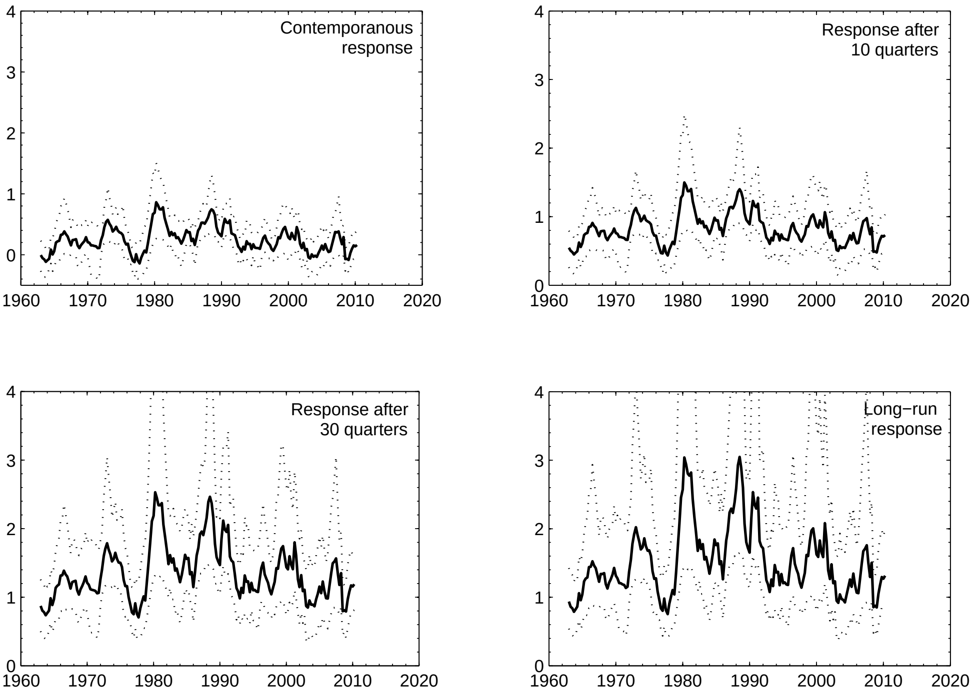
$$\mathbf{B_t} = \mathbf{\Omega_t^{1/2}} = \mathbf{A_{0,t}^{-1}H_t}.$$

The MCMC draws of $\mathbf{A_{0,t}}$ and $\mathbf{H_t}$ can therefore be directly transformed into draws of $\mathbf{B}_t$ and hence impulse responses.

[19] Alternatively, the more efficient method of Durbin [2002] could be used.

[20] Admittedly, this assumption is more controversial and could just as well be reversed. That said, when I attempted this, results remained similar.

FIGURE 3.1. Inflation Activism



Inflation activism: median response of interest rate to a 1pp permanent increase in inflation. 16th and 84th percentiles, corresponding to one standard deviation confidence bounds, are also depicted. Panel (a) shows the contemporaneous response; Panel (b) the cumulative response after 10 quarters; Panel (c) the response after 30 quarters; and finally, Panel (d) the estimate of monetary policy activism.

3.4. **Empirical Results.** The TVC-BVAR with SV is applied to estimate US monetary policy activism from January 1953 to October 2010.[21] Two lags are used in the estimation.[22] I initialize the priors using the first 10 years (120 observations) as a training sample. The estimation is based on 30,000 runs of the Gibbs Sampler, discarding the first 6,000 to allow for convergence to the ergodic distribution. To reduce the serial correlation in the draws, I save only every third draw. Appendix C shows that the model satisfies all standard convergence diagnostics.

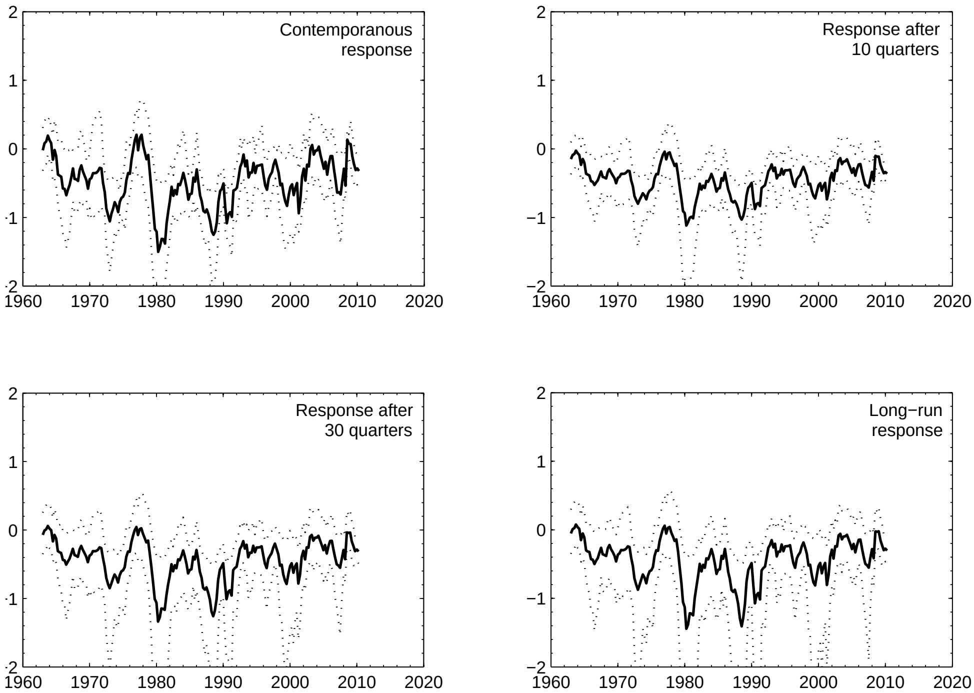
Figure 3.1 and 3.2 present the activism estimates, α_t^π and α_t^u, as well as the contemporaneous and 10/30-period impact of a permanent shock to inflation and unemployment.[23] Judging by the point estimates in panel (d), US monetary policy was "inflation active" by the mid-1960's, turned passive in the late 1970's under the chairmanships of Arthur F. Burns and G. William Miller only to become highly

[21] All series are taken from the FRED database. Inflation is measured using the annual growth rate in CPI-U, while the nominal interest rate used is the yield on 3-month Treasury bills, preferred to the more conventional policy rate as it is available for a longer period of time. The unemployment rate is measured using the civilian unemployment rate. All data is seasonally adjusted.

[22] In theory, the lag length could be optimized by calculating Bayes' factor for competing models. That said, as shown by Lindley [1957], strange outcomes can occur when using diffuse priors. Using the formula from footnote 16, the total number of parameters, including initial values is 267.

[23] The persistence of interest rates causes the variance of the posterior distribution of inflation and unemployment activism to increase rapidly. In addition, in Figure 3.1 and 3.2 I do not include uncertainty about the future evolution of the parameters. By doing so, I follow the literature and in particular the arguments given in Koop et al [2009]. Given the high dimensionality of the model, it should also come as no surprise that the standard error bands of the contemporaneous impact coefficients are reasonably wide.

FIGURE 3.2. Unemployment Activism



Unemployment activism: median response of interest rate to a 1pp permanent increase in the unemployment rate. 16th and 84th percentiles are also depicted. Panel (a) shows the contemporaneous response; Panel (b) the cumulative response after 10 quarters; Panel (c) the response after 30 quarters; and finally, Panel (d) the estimate of monetary policy activism.

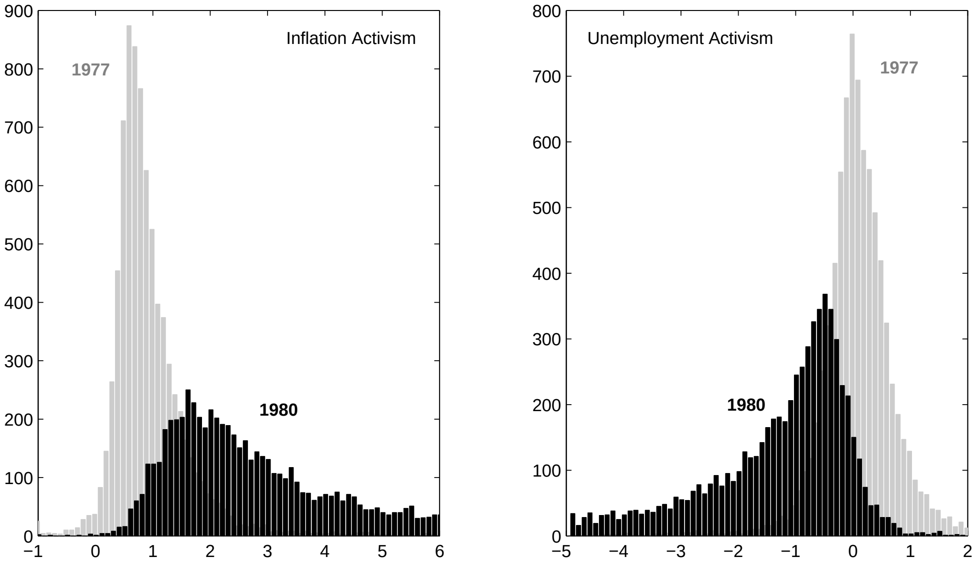
active with the arrival of Paul A. Volcker. Since then monetary policy has mostly abided by the Taylor Principle.[24] Interestingly though, inflation activism fell quite markedly during the boom years in the mid-1990s and in the early 2000s, touching marginally below the Taylor Principle recommended lower-bound of one in 2002-2003. As documented by Cogley and Sargent [2003], the 1990s and the early 2000s were characterized by unusually steady inflation rates, exhibiting high degrees of mean reversion, possibly explaining part of this decline. Finally, the large drop in inflation activism during the recent crisis is due to the policy rate reaching the lower bound.

As we can see from Figure 3.2(d), unemployment activism exhibits broadly the same trends as inflation activism. In fact, the correlation between changes in the median of α_t^{π} and α_t^{u} is -0.87, suggesting that changes in activist policies are occurring roughly at the same time. On balance this finding is consistent with innate preferences being a driver of monetary policy activism, but other factors could also explain this correlation (see more below). That said, for unemployment the difference between the long-run response and the contemporaneous response is relatively small, indicating that the Federal Reserve responds quicker to increases in unemployment than to inflation. A likely explanation for this difference is that the noise-to-signal ratio is higher for inflation than for unemployment.

Figure 3.3 plots histograms of the posterior distribution of α_t^{π} and α_t^{u} given the data during the chairmanship of Burns (January 1977) and Volcker (January

[24]This fact perhaps indicates some degree of learning from the experiences during and pre-Arthur F. Burns, see DeLong [1997] and Romer and Romer [2002].

FIGURE 3.3. Histogram for α_t^π and α_t^u in selected years



For each year, the posterior distribution of January is depicted.

1980) . The probability that $\alpha_t^\pi \geq 1$ is 0.29 and 0.94 in 1977 and 1980, respectively, indicating a reasonably large shift in the distribution. Comparing estimates along the same sample path, the probability that α_t^π increased and α_t^u decreased between 1977 and 1982 is 0.96 and 0.92, respectively. I interpret this as reasonably strong evidence - although not statistically conclusive - for a shift in policy activism between the two dates.[25]

Examining the breakdown of α_t^π and α_t^u into its estimated subcomponents $\rho_t(1)$, $\tilde{\phi}_t(1)$ and $\tilde{\psi}_t(1)$ shows that most of the variation in monetary policy activism is driven by changes in $\tilde{\phi}_t(1)$ and $\tilde{\psi}_t(1)$ (above 75% of the total variation for both α_t^π and α_t^u) rather than changes in the persistence of interest rates, $\rho_t(1)$. In fact, the sum of the estimated persistence parameters stays remarkably constant in our sample at around 0.90, despite the existence of a tentative positive covariance between $\rho_t(1)$ and α_t^π and α_t^u.[26]

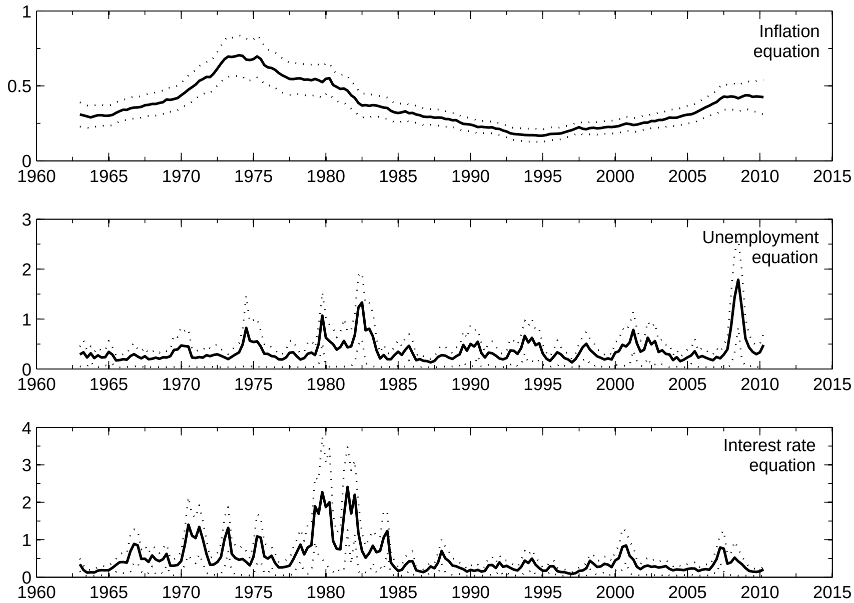
Lastly, to assess the validity of including stochastic volatility, Figure 3.4 shows the time-varying standard deviation of identified shocks. Panel (a) clearly shows the impact of the two oil price spikes, whereas in panel (c) we can see the effects of Volcker's monetary targeting. On balance, the standard error bands are fairly tight, suggesting significant variation in the standard deviation of the shocks. For instance, comparing estimates along the same sample path, the probability that the standard deviation of the interest rate equation increased from January 1977 to October 1979 is 0.96. Allowing for stochastic volatility therefore appears important when modelling monetary policy activism.[27]

[25]As noted by Cogley and Sargent [2005] and Anderson et al [2003], formal tests of time-variation provide virtually no help in establishing time-variation in VARs; the power of the tests used by Bernanke and Mihov [1998] is often below 50%.

[26]These results corroborate with the empirical findings of Boivin (2006) as well as the theoretical results in Rudebusch [2001].

[27]A few comments should be made at this point. As previously mentioned, including SV is biasing the results from finding significant time-movement in monetary policy activism by allowing some of the variation in the data to be explained by heteroskedasticity in the errors. The downside of this approach is that I increase an already sizable parameter space. That said, I simulated

FIGURE 3.4. Standard Deviation of Identified Shocks



Standard deviation of identified shocks using a Cholesky ordering on: $\mathbf{y_t} = [\pi_t,\ u_t,\ i_t]'$. Mean, 16th and 84th percentiles of the posterior distribution of the residuals are depicted. Panel (a) shows the residual standard deviation of the inflation equation; Panel (b) the unemployment equation and Panel (c) the interest rate equation.

3.4.1. *Robustness.* Overall, the results presented in the previous subsection appear reasonably robust to the choice of priors, variables, estimation sample and to whether "exogenous" measures of expectations are used. I experimented with even flatter priors for the initial states, $\mathbf{A^0}$, $\mathbf{a^0}$ and $\mathbf{h^0}$, and obtained virtually identical results. That said, the choice of priors for the hyper-parameters, given by the multiplicative factors, k_a and k_A, and the corresponding degrees of freedom, $\underline{v}_A$ and $\underline{v}_{a,i}$, $i = 1, \ldots S$, appears more important. This should come as no surprise as these parameters govern the prior belief about the amount of time variation in α_t^{π} and α_t^{u}. The parameter, $\underline{v}_A$, can be increased or decreased in the interval [20; 100] with virtually no changes in the results. However, the vector $\underline{\mathbf{v}}_\mathbf{a}$ cannot be increased to more than $[5,\ 6]'$ before the amount of time-variation starts to dwindle. I also experimented with higher/lower values for k_a and k_A and found the results to be reasonably robust, although the model starts to misbehave for much higher values of k_A (factor of 10 larger and above).

There are two main reasons for the exact choice of priors used. First, all of the previous literature, ranging from Cogley and Sargent [2001] to Koop et al [2009], have used identical priors (but all on slightly different data sets). The primary supporting argument in each case being the results of Primiceri [2001] who shows that the calculation of Bayesian factors tends to support this set of priors. Second, I conducted a grid search over the 'crucial' parameters, k_a, k_A and $\underline{v}_A$, $\underline{\mathbf{v}}_\mathbf{a}$,

the model using the time series characteristics of inflation and unemployment and found that including SV in a model which *does not exhibit it* often had only a minor impact on the estimates of $\mathbf{A^T}$ and $\mathbf{a^T}$. In addition, changes in the standard deviation of identified shocks were - rightly so - insignificant. However, excluding SV from a model which *does exhibit it* made the estimates of $\mathbf{A^T}$ and $\mathbf{a^T}$ behave quite oddly, often implying estimates far from the true values. These results are in line with Sims [2001] as well as the theoretical findings in Anderson et al [2003] and confirm the risks of excluding stochastic volatility in a model of monetary policy activism.

gradually tightening the priors more and more, and found that for a reasonably large range around the priors used the model does not misbehave and the results remain similar.[28] As the priors used are amongst the least informative in the grid, their choice appears satisfactory.[29]

In addition, I also estimated the model using different measures of inflation (the core PCE deflator and the GDP deflator) and spare capacity (linearly and HP-detrended output). The estimates of monetary policy activism in each case remained very similar; in particular when comparing estimates of α_t^π and α_t^u using linearly-detrended output with those in the baseline case. Finally, as Appendix B shows, the results presented in this section also carry through to a Taylor-Rule setting allowing for "exogenous" measures of expectations (derived from Greenbook forecasts).

3.4.2. *Comparison to other approaches.* As the literature review in the introduction describes, alternative methods to estimate US monetary policy activism have been considered in the literature. Broadly speaking, the alternative methods can be classified into three categories: (1) estimated DSGE models using TVC-VARs as in Canova et al [2008] and Villaverde et al [2010]; (2) direct estimation of time-varying Taylor Rules using Kalman Filter techniques and either ML or QLR-estimation as in Kim and Nelson [2006] and Boivin [2006]; and finally, (3) TVC-BVAR *without* stochastic volatility as in Cogley and Sargent [2001]. On balance, the estimates of inflation activism presented in this paper resemble those of Villaverde et al [2010] and Boivin [2006], while indicating somewhat more variation than found in Canova et al [2008], Kim and Nelson [2006] and Cogley and Sargent [2001]. In addition, our results resemble those of Primiceri [2005] and Cogley and Sargent [2005], both of which use TVC-BVARs with SV. That said, the estimates in this paper imply substantially less policy activism in the early 2000s than otherwise seen in the literature, possibly due to the use of additional observations.

4. Testing Brainard's Hypothesis

In this section, I estimate the impact of time-varying economic uncertainty on monetary policy activism. A first glance at the data reveals a positive contemporaneous correlation between changes in economic uncertainty and changes in monetary policy activism ($\hat{\rho}_{\Delta unc,\Delta\alpha^{\pi,m}} = 0.22$ and $\hat{\rho}_{\Delta unc,\Delta\alpha^{u,m}} = -0.14$). These initial estimates therefore suggest that the Hansen and Sargent Principle best explains Federal Reserve behavior. To investigate this relationship further and to control for any possible endogeneity, I use a Two-Stage Least Squares [TSLS] approach, instrumenting economic uncertainty with lagged values. The latent factor approach used to extract time-varying economic uncertainty rationalizes the choice of these instruments.

4.1. **Empirical Specification.** To fix ideas, consider a linear model relating the change in the median of monetary policy activism, $\Delta\alpha_t^{\pi,m}$ and $\Delta\alpha_t^{u,m}$, to changes in economic uncertainty, Δunc_t:[30]

---

[28]The grid was constructed as: $\underline{v}_A \epsilon \{[20:20:100]\}$, $\underline{\mathbf{v}}_{\mathbf{a}} \epsilon \{[2,\ 3]:[1,\ 1]:[6,\ 7]\}$, $k_a \epsilon \{[0.05:0.05:0.15]\}$ and $k_A \epsilon \{[0.005,\ 0.01,\ 0.05]\}$

[29]The model does though appear to be more robust when estimated prior to the recent financial crisis. In addition, I attempted to use a revolving barrier as in Cogley and Sargent [2005], rejecting all draws where the IRFs are unstable. This mechanism should address the previously mentioned concern about a random walk hitting any lower and upper bound with positive probability. The amount of draws rejected constituted a minute fraction of the overall number of draws and the results therefore appear very similar.

[30]Note that as Section 2 used a random walk assumption for the time-varying coefficients, the natural focus of this section is on *changes* in the parameter estimates. Standard unit root tests

$$\Delta\alpha_t^{j,m} = \beta_0^j + \beta_1^j \Delta unc_t + \mathbf{x_t'}\boldsymbol{\beta_2^j}(L) + e_t^j, \quad j = \{\pi,\, u\}\,, \tag{4.1}$$

where $\mathbf{x_t} = \left[\mathbf{cb_t'},\, \mathbf{d_t}',\, \Delta f_t,\, \tilde{\pi}_t,\, \tilde{u}_t\right]'$ denotes a vector of controls; $\mathbf{cb_t}$ a set of dummies accounting for changes in the chairmanship of the Board of Governors (to control for policy preferences)[31]; $\mathbf{d_t}$ a vector specifying changes in the formal policy framework[32]; and Δf_t, a variable proxying changes in financial instability. $\tilde{\pi}_t$ and $\tilde{u}_t$ denote indicator variables taking the value one when their Hodrick-Prescott [HP] detrended level rises significantly above the mean.[33] $\tilde{\pi}_t$ and $\tilde{u}_t$ are included in $\mathbf{x_t}$ to control for the possibility that as inflation rises significantly above the underlying rate - and/or unemployment falls below the NAIRU - policy makers might become increasingly active to avoid further changes. Surico [2008] and Curkierman and Muscatelli [2008] both find some (weak) evidence of non-linearity in the Taylor Rule, potentially causing such effects.[34]

In the following, I assume that the variables included in $\mathbf{x_t}$ - except for Δf_t - are uncorrelated with the error term, e_t^j. First, changes in the chairmanship of the Board of Governors, $\mathbf{cb_t}$, are determined by the President and the Senate at a fixed date every four years, unrelated to current economic conditions, as stipulated by the Banking Act of 1935. Second, changes in the policy framework, $\mathbf{d_t}$, due to for instance a lack of success with the previous setup, might affect monetary policy activism. But it is unlikely that changes in $\alpha_t^{j,m}$, not attributed to the variables in our model, can alter the target variable within the month. Lastly, inflation and unemployment are according to VAR studies impacted by changes in monetary policy at roughly a six month to two year frequency, see e.g. Christiano et al [2001]. It is therefore doubtfull that changes in the error term, respresenting for instance changes in a given governor's innate preferences, can immediately impact them.

A problem with directly estimating (4.1) is the possibility of feedback between changes in monetary policy activism, $\Delta\alpha_t^{j,m}$, and changes in economic uncertainty, Δunc_t. Even at a monthly frequency, it is plausible that changes in the behavior of monetary authorities impact contemporaneously the amount of economic uncertainty. A similar feedback could also exist between changes in monetary policy activism and changes in financial fragility, Δf_t. That said, inferring a change in policy activism might under normal circumstances take more than a month for the public, suggesting that the possible endogeneity in (4.1) is by no means certain. Moreover, Federal Reserve meetings have pre-dominantly taken place towards the end of the month (74% after the 18th day), indicating some attenuation to any possible endogeneity bias. Comparing Instrumental Variables [IV] estimates with Least Squares [LS] results will help clarify the likelihood of this feedback mechanism.

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also indicate that the I(1) assumption for both inflation and unemployment activism cannot be rejected at the one percent level.

[31]The sample covers the chairmanship of William M. Martin, Arthur F. Burns, G. William Miller, Paul A. Volcker, Alan Greenspan and Ben S. Bernanke.

[32]I account for the switch to non-borrowed reserve targeting in October 1979 as well as the subsequent switch (back) to Federal Funds Rate targeting. Unfortunately, the exact date for the latter is difficult to infer. Thornton [2005], using transcripts of the "Blue Book" and the "Report of Open Market Operations", finds that October 1982 is the most likely date. October 1982 is therefore set as the end-date to money supply targeting.

[33]Both variables are HP-detrended with $\lambda = 129,600$. The threshold used is ± 1.65 standard deviations above the mean, corresponding to a ten percent two-sided significance level, treating each month as an independent observation (see Bloom [2009]).

[34]To see that non-linearity in the Taylor Rule can cause these effects, consider a simple regression model with a quadratic term (using standard notation): $y_t = x_t\beta + x_t^2\gamma + \epsilon_t = x_t\left[\beta + x_t\gamma\right] + \epsilon_t = x_t\tilde{\beta}_t + \epsilon_t,\ \tilde{\beta}_t = \beta + x_t\gamma$.

To instrument for changes in economic uncertainty at time t, I use the lagged values: unc_{t-1} and unc_{t-2}. The AR(2) specification used in the latent factor approach to extract time-varying economic uncertainty, unc_t, combined with highly significant coefficients on both AR terms ($p - values < 0.01$), implies that the lagged values are highly correlated with changes in economic uncertainty at time t.[35] In addition, it is plausible that monetary policy makers respond to changes in economic uncertainty as soon as possible, rather than respond to lagged changes; in particular given the evidence in Hansen and Sargent [2007] of fairly large welfare gains to applying robustly optimal policy rules. The instruments should therefore also be uncorrelated with the error term.[36] The instrument set for Δf_t analogously includes: Δf_{t-1}, Δf_{t-2} and two lags of the unemployment rate. The use of lagged values as instruments is common in macroeconomics and is, for instance, in line with the literature estimating New-Keynesian Phillips Curves, see Clarida and Gertler [1999].

Finally, the presence of "generated regressors" in (4.1) implies a need to correct the standard errors of the estimates. Following Bernanke, Boivin and Eliasz [2005], I implement a standard residual-based boot-strap procedure that accounts for the uncertainty in the factor estimate of Δunc_t.

4.2. **Baseline Results.** Table 2 presents IV and LS estimates of equation (4.1) excluding and including changes in financial instability, Δf_t. Financial instability, f_t , is proxied using the TED spread: the spread between three-month US Treasury Bills and the corresponding maturity USD LIBOR rate, available from November 1984.[37] The estimation sample is thus from January 1965 to October 2010 and from December 1984 to October 2010, respectively. Zero lags are used in the estimation.

Contrary to Brainard's Principle, the results in Table 2 indicate that an increase in aggregate economic uncertainty, $\Delta unc_t > 0$, has in absolute terms a positive and significant effect on monetary policy activism. In fact, across all specifications the Hansen and Sargent Principle is a better explanation of actual Federal Reserve behavior. The estimates of the impact of uncertainty on inflation activism range in between 0.092 and 0.271, implying that a two standard deviation increase in economic uncertainty, roughly what was witnessed during the recent crisis, has a positive impact on the long-run responsiveness to inflation of 0.184 to 0.542, all else equal - an economically meaningful amount.[38] Interestingly, an estimate of the long-run change in the responsiveness to inflation of c. 0.250 is in accordance with the original simulations in Sargent [1999], although it is difficult to directly compare increases in our uncertainty proxy with the risk-sensitivity measure used by Sargent. The estimates of the impact of a change in uncertainty on unemployment activism range from -0.054 to -0.172. The Federal Reserve therefore appears to respond, on average, to increases in economic uncertainty with assigning a relatively larger weight on inflation in the Taylor Rule. This may seem like a slightly counter-intuitive result: Hansen and Sargent [2007] find the opposite effect in a

[35]To see this result, note that any AR(2) process, $y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \epsilon_t$, can be written as: $\Delta y_t = [\phi_1 - 1]\, y_{t-1} + \phi_2 y_{t-2} + \epsilon_t$. The R^2 of a regression of Δunc_t on unc_{t-1} and unc_{t-2} is 0.58. In addition, "first stage" projection coefficients can be taken directly from the estimates in Section 2. The "second stage" variance matrix still needs to be adjusted though for the use of instruments.

[36]Including lagged values of uncertainty in the LS estimates presented below supports this assertion: despite the multicolinearity, the lagged values appear statistically insignificant.

[37]The TED spread is the standard measure of the US bank risk premia, and is thus an often used proxy of financial instability.

[38]To put this number in context, 0.5 is about the difference between the level of inflation activism seen under Arthur F. Burns and the average level under Ben S. Bernanke, see Section 3.

small theoretical model.[39] That said, the difference between the parameter estimates is not large, especially when taking into account the uncertainty surrounding the estimates.

Comparing the impact of changes in uncertainty across specifications in Table 2, we see that the LS results are smaller than the IV estimates, indicating some downward bias, though the difference is not statistically significant. Controlling for financial instability, on the other hand, as in column (2) and (4), appears to make activism respond more, in an absolute sense, to economic uncertainty. However, this effect may partially be attributed to the different samples used as the preferred measure of financial instability, the TED spread, is only available from December 1984 onwards.

In sum, the results in Table 2 provide reasonably compelling evidence of the Federal Reserve acting according to the Hansen and Sargent Principle: increasing monetary policy activism in response to positive shocks to economic uncertainty. Robust control consideration may therefore contain a descriptive content yet to be fully acknowledged in the literature. That said, central bank experimentation can appear to (slightly) dull the incentive for a Brainard type response (Wieland [1998, 2006]), perhaps explaining a proportion of these findings. However, as argued by Svensson and Williams [2007], for most models the experimentation motive may not be of a practical concern; and in either case, it is difficult to find historical evidence of actual Federal Reserve experimentation.

Table 2 offers additional insight into the other determinants of monetary policy activism. Changes in financial instability, Δf_t, have a negative effect on monetary policy activism, implying that more financial instability, all else equal, makes monetary policy makers more timid. However, this effect is only statistically significant at the ten percent level, and is in all specifications less than a third of the effect of economic uncertainty. There is thus some tentative evidence that increases in financial instability cause a shift away from inflation and output stabilization; perhaps towards providing added liquidity to the banking sector. That said, Δf_t and Δunc_t do exhibit some moderate positive correlation ($\hat{\rho} = 0.27$), which might also (partially) explain these findings. To investigate the robustness of the tentative negative impact of financial fragility on monetary policy activism, in the following subsection, I use a different proxy for Δf_t, available back to January 1973.

The dummy accounting for the chairmanship of Paul A. Volcker is borderline statistically significant across all specifications in Table 2, but economically of a smaller magnitude than perhaps expected. In the following subsection, I show that this can partially be explained by the use of monthly data. But also the fact that I control for changes in the policy framework enacted by Volcker, specifically the start of non-borrowed reserve targeting, contributes to this result. The remaining dummies in $\mathbf{cb_t}$, accounting for changes in the chairmanship of the Board of Governors, are all insignificant. This corroborates with the results in Section 2, showing that changes in activism *within* chairmanship terms are at least as large as changes in activism *across* chairmans.

[39] One explanation of the relatively larger weight placed on inflation could be that changes in uncertainty cause changes in the central bank loss function, assigning a higher weight to inflation. This could be the case if, for instance, the credibility of the price stability mandate was structurally smaller than the credibility of the output mandate. An increase in uncertainty would thus cause the central bank to react relatively more to inflation in order to attempt to maintain/increase the credibility of the inflation target.

TABLE 2. Results from Baseline Specifications

	Inflation Activism				Unemployment Activism			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Constant	-0.002	-0.003	-0.003	-0.005	0.001	0.002	0.001	0.002
	(0.003)	(0.004)	(0.003)	(0.005)	(0.002)	(0.003)	(0.002)	(0.003)
Burns	0.028	-	0.028	-	-0.021	-	-0.023	-
	(0.059)		(0.061)		(0.037)		(0.040)	
Miller	-0.056	-	-0.056	-	0.028	-	0.028	-
	(0.060)		(0.061)		(0.038)		(0.039)	
Volcker	0.110**	-	0.095*	-	-0.063*	-	-0.068*	-
	(0.059)		(0.059)		(0.037)		(0.041)	
Greenspan	0.012	0.005	0.011	0.042	-0.004	-0.006	-0.003	-0.023
	(0.062)	(0.071)	(0.069)	(0.086)	(0.034)	(0.046)	(0.037)	(0.055)
Bernanke	0.066	0.085	0.065	0.059	-0.052	-0.045	-0.042	-0.038
	(0.060)	(0.072)	(0.062)	(0.082)	(0.038)	(0.047)	(0.040)	(0.052)
ΔFramework	0.084**	-	0.154**	-	-0.056**	-	-0.056**	-
	(0.041)		(0.044)		(0.025)		(0.029)	
$\tilde{\pi}_t$	0.031**	0.008	0.029***	0.013	-0.017***	-0.007	-0.018***	-0.010
	(0.009)	(0.035)	(0.009)	(0.048)	(0.005)	(0.014)	(0.006)	(0.030)
$\tilde{u}_t$	-0.001	0.043***	-0.006	0.038**	0.006	-0.020**	0.005	-0.023*
	(0.001)	(0.013)	(0.010)	(0.016)	(0.007)	(0.010)	(0.007)	(0.013)
Δf_t	-	0.009	-	-0.084*	-	0.010*	-	0.054*
		(0.007)		(0.046)		(0.005)		(0.029)
Δunc_t	0.092***	0.110***	0.098**	0.271***	-0.054***	-0.071**	-0.064**	-0.172***
	(0.021)	(0.039)	(0.039)	(0.099)	(0.016)	(0.029)	(0.026)	(0.063)
Sample	02/65:10/10	12/84:10/10	02/65:10/10	12/84:10/10	02/65:10/10	12/84:10/10	02/65:10/10	12/84:10/10
F	13.2	8.25	-	-	6.67	7.57	-	-
R^2	0.18	0.14	-	-	0.10	0.13	-	-
p_{J-stat}	-	-	0.51	0.29	-	-	0.64	0.38

(i) Residual-based Boot-strapped standard errors in parentheses using 40,000 boot-strap loops.

(ii) * p<0.10, ** p<0.05, *** p<0.01.

(iii) Equation (1) and (2) are estimated using LS; (3) and (4) using TSLS,
instrumenting Δunc_t with unc_{t-1} and unc_{t-2}, and Δf_t with Δf_{t-1}, Δf_{t-2} and two lags of the unemployment rate.

(v) The p-values for the J-statistics assume a standard χ^2 distribution.

TABLE 3. Durbin-Wu-Hausman Tests for Exogeneity of Δunc_t

	Inflation Activism		Unemployment Activism	
	(1) and (3)	(2) and (4)	(1) and (3)	(2) and (4)
Diff. in J-stat	0.24	1.53	0.31	1.36
P-value	0.63	0.20	0.52	0.24

(i) Assuming the test size follows a $\chi^2(1)$.

Finally, the inflation variable, $\tilde{\pi}_t$, is significant in column (1) and (3), while the unemployment variable, $\tilde{u}_t$, is significant in column (2) and (4). In either case, a "large" spike triggers a more activist response. Although the economic impact is not large, the effect is present regardless of how I control for inflation and unemployment. Extra-ordinary economic situations, such as large recessions or inflation spikes, therefore appear, all else equal, to cause more activist policies. This partially corroborates with the evidence of some (weak) non-linearity in the Taylor Rule (Surico [2008] and Curkierman and Muscatelli [2008]).

I started this section assuming that monetary policy activism was endogenous within the month. This assumption can, however, (normally) be tested. Table 3 provides the Durbin-Wu-Hausman Test for the exogeneity of Δunc_t. As we can see, Δunc_t does in fact *appear* to be exogenous. However, in this case the test-size follows an unknown distribution, rather than the standard $\chi^2(1)$, as the use of "generated-regressors" renders the Durbin-Wu-Hausman test invalid. Despite the relatively large differences in J-stat values, I therefore choose to report TSLS results throughout.

4.3. **Robustness Analysis.** In this subsection, I investigate the robustness of the previous results along two dimensions: (1) alternative measures of activism, uncertainty and financial instability; and (2), different subsamples and frequency. I demonstrate that in each instance, the basic insights from the baseline case remain broadly intact.

4.3.1. *Alternative Measures.* I re-estimate equation (4.1) using different measures of monetary policy activism, uncertainty and financial instability. As an alternative gauge of monetary policy activism, I consider the measure estimated in Appendix B using real-time Greenbook data. The alternative measure of uncertainty used is an indicator variable measuring "large spikes" in unc_t. Bloom [2009] argues that large spikes in uncertainty are likely to have proportionally much larger real effects due to non-linearities in the "wait-and-see" effects.[40] Lastly, I also consider an alternative proxy for financial instability, available back to January 1973: the "Adjusted Financial Stability Index" developed by Brave and Butters [2011] and published weekly by the Chicago Federal Reserve.[41]

Table 4 reports the estimates. The key result from the baseline case - that monetary policy activism responds positively to increases in economic uncertainty - is robust to the use of alternative variables. In fact, for almost all parameter estimates the sign and magnitudes remain within the range of our baseline findings. There are, however, some differences. Most importantly, the alternative measure

[40]The economic uncertainty measure, unc_t, is HP-detrended with $\lambda = 129,600$. Absolute values outside the threshold (± 1.65 standard deviations above the mean) are coded as one. This corresponds to using a ten percent two-sided significance level, treating each month as an independent observation. For more on this approach, see Bloom [2009].

[41]The "Adjusted Financial Stability Index" is the first latent factor of a set of 100 variables comprised of: (1) spreads between various interest rates measuring market risk-premia and liquidity conditions; (2) surveys of the tightness of loan standards; and (3), variables measuring the size of total banking assets and commercial deposits.

TABLE 4. Alternative Measures

	Δf_t	Δunc_t	Sample
Alternative $\Delta\alpha_t^{j,m}$			
Inflation	-0.027	0.244**	12/84:12/05
	(0.049)	(0.117)	
Unemployment	0.009	-0.076	12/84:12/05
	(0.034)	(0.081)	
Indicator unc_t			
Inflation	-0.024	0.146***	12/84:12/07
	(0.036)	(0.034)	
Unemployment	0.031	-0.089***	12/84:12/07
	(0.023)	(0.022)	
Alternative Δf_t			
Inflation	0.051*	0.163**	01/73:10/10
	(0.031)	(0.068)	
Unemployment	-0.032	-0.106**	01/73:10/10
	(0.022)	(0.043)	

(i) Estimated using TSLS, instrumenting Δunc_t with unc_{t-1} and unc_{t_2}, and Δf_t with Δf_{t-1}, Δf_{t-2} and two lags of the unemployment rate.
(ii) $j = \pi,\ u$
(iii) Residual-based Boot-strapped standard errors in parentheses using 40,000 boot-strap loops.
(iv) * p<0.10, ** p<0.05, *** p<0.01.

of unemployment activism still responds negatively to economic uncertainty, but the estimate is no-longer statistically significant. The difference between the effect of uncertainty on the two measures of unemployment activism is in line with the discussion in Appendix B, suggesting slightly larger discrepancies between the two estimates of $\alpha_t^{u,m}$ than of $\alpha_t^{\pi,m}$. The estimates of the impact of the alternative financial instability measure are again only borderline statistically significant; however, they are of the opposite sign compared to the baseline case, implying some (weak) evidence that financial instability also causes a more active policy. Finally, the sample for the estimates using the indicator uncertainty variable is shrunk to avoid contaminating the results with a policy that reaches the zero lower bound.[42]

[42]The estimates including the recent crisis are 0.06 and -0.03 for inflation and unemployment activism, respectively. Both are borderline significant at the ten percent level. The recent crisis is the last time the indicator variable for uncertainty hits one; however, in this case policy cannot become more active as it is already at the zero lower bound. Given the limited variability in the uncertainty indicator series, as well as the limited sample, it therefore makes sense that the standard errors will increase and coefficient estimates decrease (in an absolute sense) when compared to the estimates excluding the crisis.

TABLE 5. Different Subsamples and Frequency

	Δf_t	Δunc_t	Sample
Pre-1985			
Inflation	0.027	0.051	01/75:01/85
	(0.026)	(0.032)	
Unemployment	-0.021	-0.039	01/75:01/85
	(0.018)	(0.033)	
Post-1985			
Inflation	0.010	0.215**	02/85:10/10
	(0.034)	(0.009)	
Unemployment	-0.010	-0.159**	02/85:10/10
	(0.022)	(0.079)	
Quarterly data			
Inflation	0.013	0.210**	Q1/85:Q3/10
	(0.010)	(0.101)	
Unemployment	-0.009	-0.128*	Q1/85:Q3/10
	(0.011)	(0.065)	

(i) Estimated using TSLS instrumenting Δunc_t with unc_{t-1} and unc_{t-2}, and Δf_t with Δf_{t-1}, Δf_{t-2} and two lags of the unemployment rate.
(ii) Residual-based Boot-strapped standard errors in parentheses using 40,000 boot-strap loops.
(iii) * $p<0.10$, ** $p<0.05$, *** $p<0.01$.
(iv) To make pre and post estimates comparable, the "alternative" financial instability measure is used.
(v) Quarterly estimates include three ma-terms.

In sum, the key insight provided by our baseline estimates - that monetary policy activism responds positively to changes in economic uncertainty - is robust to alternative measures of financial instability and uncertainty, and broadly robust to the alternative measure of monetary policy activism considered.

4.3.2. *Alternative Subsamples and Frequency.* I next explore the stability of the estimates with regards to different subsamples and the frequency of data.

In Figure 2.1, we saw that changes in US macroeconomic uncertainty where on average larger before 1985 than after (with the obvious exception being the recent crisis). In addition, our baseline results showed somewhat larger coefficients on economic uncertainty in the shorter sample [columns (2) and (4) in Table 4.1], roughly corresponding to the Great Moderation. It is therefore interesting to see whether the responsiveness to changes in economic uncertainty has changed from "pre-Great Moderation" to "post-Great Moderation". Table 5 reports the estimates.[43] As we can see, monetary policy activism appears to respond significantly more to changes

[43] To make pre and post estimates as comparable as possible, the "alternative" financial instability measure from subsection 4.3.1 is used.

in economic uncertainty after the start of the "Great Moderation": the coefficient on Δunc_t is statistically insignificant and economically smaller in the "pre-Great Moderation" sample. Moreover, for inflation activism, a Quandt-Andrews Breakpoint Test gives a maximum Wald F-statistic [QUF] of 8.01 in October 1989. Unfortunately though, the asymptotic distribution of the test-size is unknown due to the presence of "generated regressors", so it is difficult to assess the statistical significance of this.[44] In addition, as pointed out by Cogley and Sargent [2001], the power of the QUF test is often very low, in particular when estimated over a relatively small subsample. These results should therefore be viewed accordingly. Nonetheless, the estimates are puzzling and could potentially indicate a shift in the responsiveness of the Federal Reserve to economic uncertainty.

I complete the robustness analysis by reporting estimates of equation (4.1) using quarterly data. As an instrument for economic uncertainty, unc_t^Q, I again use the lagged values unc_{t-1}^Q and unc_{t-2}^Q, but this time point-sample them at the first month of the quarter to reduce any endogeneity problems. Table 5 reports the corresponding results. For both inflation and unemployment activism, the results are qualitatively and quantitatively similar to the baseline case. That said, financial instability now appears with a positive coefficient - as with the alternative measure of f_t - indicating that a higher degree of financial instability leads to a more active policy. The dummies used in the quarterly specification to account for switches in the chairmanship of the Board of Governors are now also estimated to have a larger impact. For instance, the dummy accounting for the switch to Ben S. Bernanke from Alan Greenspan is estimated to be 0.265 and significant at the five percent level

In sum, the key insights presented in the baseline case are robust to changes in the frequency of the data. Subsample estimates, however, suggest that the Federal Reserve has perhaps responded more forcefully to changes in economic uncertainty after the start of the "Great Moderation".

5. Conclusion

This paper addresses the question: does US monetary policy activism depend on economic uncertainty? In particular, I investigate whether US monetary policy makers have reacted according to the Brainard Principle (stating that policy should exhibit conservatism in the face of uncertainty) or the Hansen and Sargent Principle (stating that policy should be more aggressive when economic uncertainty increases). Contrary to the prescription in Brainard's [1967] seminal paper, my estimates indicate a significant Hansen and Sargent type reaction. Long-run coefficients on inflation and unemployment in a Taylor Rule increase by in between 0.1 and 0.5 in response to a two standard deviation increase in economic uncertainty, roughly what was witnessed during the recent crisis.

To determine the effect of uncertainty on monetary policy activism, I follow a three-step strategy. I first construct a measure of aggregate economic uncertainty using five proxies and the method proposed by Giannone et al. [2008]. Second, using a TVC-BVAR with SV, I estimate monetary policy activism. I detect sizable variation in the responsiveness of the Federal Reserve. In particular, there appears to be a large trend decrease in activism during the tenure of Alan Greenspan - sometimes even touching the Taylor Principle lower-bound. Lastly, to analyze the impact of economic uncertainty on monetary policy activism, I employ a simple TSLS approach.

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[44] Using - incorrectly - the Hansen [1997] tabulated asymptotic distribution gives a p-value of 0.079 (15% trimmed data). Interestingly, the maximum Wald F-statistic for unemployment activism is not until December 1998.

The two key insights from this analysis are: inflation activism responds positively to economic uncertainty across all specifications. Moreover, this effect is economically and statistically significant, often implying changes in activism similar to the average difference between the chairmanships of Ben S. Bernanke and Arthur F. Burns. Unemployment activism similarly appears to respond positively to aggregate uncertainty; however, the effect is across most specifications slightly smaller and appears to depend more on the exact measure of activism employed.

A central limitation of this paper is the reliance on specific measures of activism and uncertainty. As Anderson et al [2003] points out, detecting significant evidence of time-variation in the systematic parts of linear equations is difficult - at least when compared to detecting stochastic volatility - and the results presented should be interpreted accordingly.

In closing, an important question this paper raises but does not answer is: what type of a response to uncertainty would empirically have been better? The Hansen and Sargent approach - or the Brainard type. In addition, central bank "experimentation" as well as non-linear responses could perhaps slightly dull or amplify the coefficient estimates presented here. Future work should attempt to incorporate these issues.

Appendix A: Uncertainty Data

Below, I outline the details of the five proxy variables used in the construction of the uncertainty measure. All data where the source is not explicitly mentioned comes from the Federal Reserve Bank of St. Louis online data base (FRED).

(1) Stock-market volatility. I use the CBOE's VXO index of implied volatility on a hypothetical S&P100 option 30 days to expiration. The VXO is available daily from January 1986. Monthly aggregates are constructed by averaging daily observations. Pre-1986, realized monthly return volatility is calculated as the standard-deviation of daily returns of the S&P500, normalized to the same mean and variance as the VXO index over the period when they overlap (1986M1-2010M10). Realized and implied volatility are highly correlated at 0.879. The US stock market was closed for four days after 9/11; the implied volatility levels for these four days were interpolated using the European VX1 index.

(2) GDP growth volatility. Estimated as the conditional standard deviation from a GARCH(1,1) specification of $log(GDP_t)$ regressed on its own four lags, a constant term and a trend. The estimation sample is from 1955Q1 to 2010Q3.[45] Quarterly data is interpolated to monthly frequency using a cubic spline. I also experimented with an ARCH(1) specification and with using the growth rate of GDP instead of the level. Either way, the results appear very similar.

(3) The cross-sectional range of output growth. Calculated from the Federal Reserve Board's G17 database on monthly output growth for NAICS level 4 manufacturing, available from January 1972. Monthly output growth is computed as: $\Delta y_{i,t}^M = \frac{y_{i,t}^M - y_{i,t-1}^M}{y_{i,t-1}^M}$. The cross-sectional range of output growth is defined as the interquartile range [IQR] on the panel of monthly growth rates.[46]

(4) Professional forecasters one-year-ahead output and unemployment dispersion. Computed as the IQR on industrial production and nationwide unemployment forecasts from the SPF database (Survey of Professional Forecasters done by the Federal Reserve Bank of Philadelphia). All forecasts used are four quarters ahead (expected) year-over-year growth rates with an average of 39 and 45 forecasters in each cross-section, respectively. The sample period is from 1968Q4 to 2010Q4. Quarterly data is interpolated to monthly frequency using a cubic spline.

(5) Producer and consumer business expectation dispersion. Calculated from the University of Michigan Surveys of Consumers (MCSI) and the Federal Reserve Bank of Philadelphia's Regional Business Outlook Survey, available from January 1978 and May 1968, respectively. The consumer based measure uses the sub-component: 'Business conditions expected during the next 12 months', whereas the producer based uses: 'Expected business conditions six months ahead'. In both cases, the uncertainty measure was defined as: $unc_t^i = \sqrt{I_t^i + D_t^i - (I_t^i - D_t^i)^2}$, where $i = cons, prod$ and I_t denotes the fraction of respondents specifying an increase and D_t the fraction specifying a decrease. unc_t^i is therefore equal to the

[45] More specifically, I estimate: $y_t = \beta_0 + t + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \beta_3 y_{t-3} + \beta_4 y_{t-4} + \epsilon_t$, where y_t denotes output, $\epsilon_t \mid \Omega_t \sim N\left(0, \sigma_t^2\right)$ and $\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_t^2 + \delta_1 \sigma_{t-1}^2$ using the Bollerslev and Wooldridge QML-method and the BHHH-algorithm (see Bollerslev [1986]).

[46] Using the cross-sectional dispersion of industrial production is a common proxy for macroeconomic uncertainty, see e.g. Bloom et al. [2010]. However, most authors compute the IQR across both sub- and main-groupings (i.e. confound level 3 and level 4 data). This is avoided in the above calculation.

cross-sectional standard deviation of the survey responses if the *increase* category is quantified by $+1$ and the *decrease* category by -1.[47]

[47] See also Bachmann et al. [2010].

Appendix B: Monetary Policy Activism: Evidence from Federal Reserve Forecasts

In this appendix, I estimate US monetary policy activism using a time-varying Bayesian regression [TVC-BR] with stochastic volatility [SV] on real-time data from the Federal Reserve. The procedure adapts the Bayesian VAR techniques laid out in the body of this paper to a single equation case. All discussions of simulation techniques will therefore be kept to a minimum.

Consider a modified, explicitly forward-looking, version of the monetary policy rule considered in Section 3:

$$i_t = \rho(L)i_{t-1} + [1-\rho(L)]\, i_t^* + e_t^{MP} \tag{5.1}$$

$$i_t^* = i^* + \phi(L)\mathbb{E}\left[\pi_{t+h} - \pi^* \mid \Omega_t\right] + \psi(L)\mathbb{E}\left[u_{t+k} - u^* \mid \Omega_t\right], \tag{5.2}$$

where π_{t+h} denotes the percentage change in the price level between periods t and $t+h$ (expressed in annual rates); u_{t+k} the average unemployment rate between periods t and $t+k$; and Ω_t, the information set at the time. Equations (5.1) and (5.2) specify that the monetary authorities set the target interest rate, i_t^*, as a function of the *expected* inflation and unemployment gap; however, they only attain the target rate gradually as they smooth the transition from one target rate to the next. Combining gives:

$$i_t = \tilde{i}^* + \rho(L)i_{t-1} + \tilde{\phi}(L)\mathbb{E}\left[\pi_{t+h} - \pi^* \mid \Omega_t\right] + \tilde{\psi}(L)\mathbb{E}\left[u_{t+k} - u^* \mid \Omega_t\right] + e_t^{MP}, \tag{5.3}$$

where $\tilde{i}^* \equiv [1-\rho(1)]\, i^*$, $\tilde{\phi}(L) \equiv [1-\rho(L)]\,\phi(L)$ and $\tilde{\psi}(L) \equiv [1-\rho(L)]\,\psi(L)$. Equation (5.3) can be interpreted as a purely forward-looking Taylor Rule, augmented to include higher-order dynamics.

Monetary policy activism with regards to inflation (α^π) and unemployment (α^u) is (again) defined as, respectively:

$$\alpha^\pi \equiv \tfrac{\tilde{\phi}(1)}{1-\rho(1)} \tag{5.4}$$

$$\alpha^u \equiv \tfrac{\tilde{\psi}(1)}{1-\rho(1)}. \tag{5.5}$$

As explained in Section 3, various approaches have been employed to estimate (5.3). In this appendix, I follow Orphanides [2001] and Boivin [2006] - where the latter also allows for time-variation in the coefficient estimates - and use, as a proxy for the Board of Governors' expectations, $\mathbb{E}_t\left[\pi_{t+h} - \pi^*\right]$ and $\mathbb{E}_t\left[u_{t+k} - u^*\right]$, the forecasts computed by the Staff of the Federal Reserve. These forecasts are published a few days before the FOMC meeting and collected with a five year lag in "the Greenbook".[48]

Besides the issues discussed in Section 3 (the potential endogeneity in (5.3) as well as the limited sample length), several other aspects of the Greenbook data need mentioning. While there is very little information on how the Greenbook forecasts have actually been constructed, it appears that from 2004 to 2005 the Federal Reserve experimented with using Random Walk forecasts of the unemployment rate. In addition, while the unemployment series has remained relatively unrevised throughout the sample period that cannot be said for GDP or the GDP deflator (note that CPI inflation is not consistently available and is therefore not used in the following). From 1969 to 1991, the Federal Reserve focused on forecasting GNP,

[48] Reifschneider, Stockton and Wilcox [1997] provide further information on the Greenbook forecasts. For a thorough discussion of the properties of the Greenbook forecast errors, see Orphanides [2002] and Romer and Romer [2004].

while GDP was preferred in between 1991 and 2001. Finally, for the last part of the sample, chain-weighted GDP was the preferred measure of aggregate activity. That said, most of the changes to the historical values appear on the real side, implying, as argued by Boivin [2006], that a spliced series of forecasts of the deflators can be used, although imperfectly so, as a measure of expected inflation.

Model. To estimate (5.3), I use a TVC-BR with SV using $y_t = [i_t]$ as the dependent variable and $\mathbf{x_t} = [i_{t-1}, \mathbb{E}_t(\pi_{t+h}), \mathbb{E}_t(x_{t+k})]'$ as the explanatory variables. Consider the model:

$$y_t = c_t + \mathbf{x'_t}\beta_{\mathbf{1,t}} + \mathbf{x'_{t-1}}\beta_{\mathbf{2,t}} + \ldots + \mathbf{x'_{t-p}}\beta_{\mathbf{p,t}} + \epsilon_t, \quad \mathbb{V}[\epsilon_t] = \sigma_t^2 \tag{5.6}$$

where c_t denotes a time varying constant; $\beta_{\mathbf{i,t}}, i = 1, \ldots, p$, an $n \times 1$ vector of time-varying coefficients; and ϵ_t, a heteroskedastic shock with variance σ_t^2. Vectorizing the RHS coefficients in (5.6) and stacking them in $\beta_\mathbf{t}$ allows us to write the equation as:

$$\begin{aligned} y_t &= \tilde{\mathbf{x}}'_\mathbf{t}\beta_\mathbf{t} + \sigma_t e_t, \quad \mathbb{V}[e_t] = 1 \\ \tilde{\mathbf{x}}'_\mathbf{t} &= \left[1, \mathbf{x'_{t-1}}, \mathbf{x'_{t-2}}, \ldots, \mathbf{x'_{t-p}}\right]. \end{aligned} \tag{5.7}$$

The dynamics of the model parameters, $\beta_\mathbf{t}$ and $\log(\sigma_t)$, are (again) assumed to follow driftless random walks, i.e.:

$$\beta_\mathbf{t} = \beta_\mathbf{t-1} + \mathbf{e}_\mathbf{t}^\beta \tag{5.8}$$

$$\log(\sigma_t) = \log(\sigma_{t-1}) + e_t^\sigma. \tag{5.9}$$

All innovations are assumed to be jointly normally distributed with covariance matrix given by:

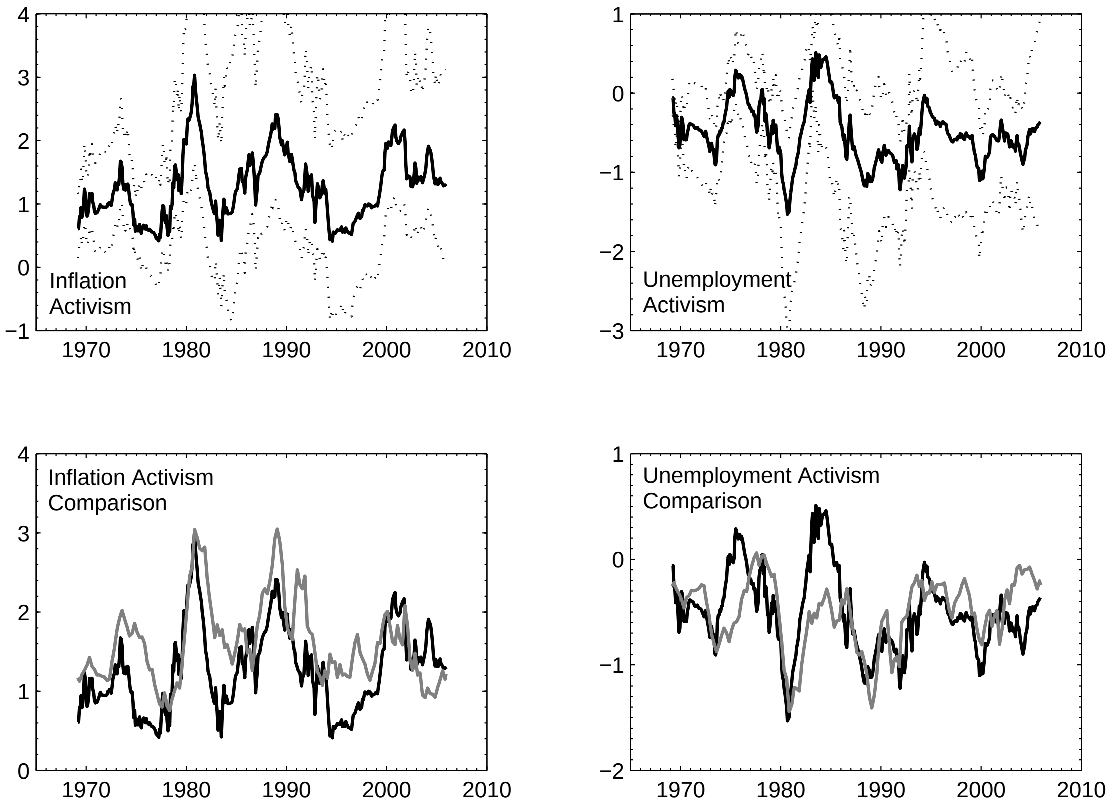
$$\mathbf{V} = \mathbb{V}\left(\begin{bmatrix} e_t \\ \mathbf{e}_\mathbf{t}^\beta \\ e_t^h \end{bmatrix}\right) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \mathbf{V}^\beta & 0 \\ 0 & 0 & V^\sigma \end{bmatrix}, \tag{5.10}$$

where $\mathbf{V}^\beta$ is a symmetric positive definite matrix and V^σ is a strictly positive number. The estimation of (5.7) subject to (5.8)-(5.10) is done using Bayesian methods. All priors are selected in accordance with Section 3. To allow for the same amount of a priori uncertainty, variance parameters for $\beta^\mathbf{0}$ are though matched to previous estimates. Hence:

$$\begin{gathered} \beta^\mathbf{0} \sim N\left(\hat{\beta}^\mathbf{LS}, 4\mathbb{V}\mathfrak{A}_\beta^\mathbf{LS}\right) \\ \log\left(\sigma^0\right) \sim N\left(\log\left(\hat{\sigma}^{LS}\right), 1\right) \\ V^\sigma \sim IW\left(2k_h, 2\right), \quad \mathbf{V}^\beta \sim IW\left(30k_\beta \mathbb{V}\mathfrak{A}_\beta^\mathbf{LS}, 30\right), \end{gathered}$$

where $k_\beta = 0.1^2$, $k_h = 0.01^2$ and $\mathbb{V}\mathfrak{A}_\beta^\mathbf{LS}$ denotes the covariance matrix of the equivalent parameters in Section 3. For details on the simulation method used, see Section 3.

FIGURE 5.1. Monetary Policy Activism Using Greenbook Forecasts



Monetary policy activism: median response of interest rate to a 1pp permanent increase in either the inflation or the unemployment rate. 16th and 84th percentiles are also depicted. Panel (a) shows inflation activism; Panel (b) unemployment activism; Panel (c) compares inflation activism estimates (median) using Greenbook forecasts (black line) with those from Section 3 (gray line); and finally, Panel (d) compares unemployment activism estimates using Greenbook forecasts (black line) with those from Section 3 (grey line). Monetary policy activism estimates using Greenbook forecasts are linearly interpolated between the FOMC meetings.

Empirical Results. Equation (5.3) is estimated using a TVC-BR with SV from March 1969 to December 2005.[49] Two lags of i_t are employed in the estimation; the other variables enter without lags. $\mathbb{E}_t\left[\pi_{t+h}\right]$ is given by the Greenbook forecast of the annualized percentage change in the GNP/GDP deflator between period t and $t+h$, while $\mathbb{E}_t\left[u_{t+k}\right]$ is given by the average of the Greenbook forecasts of the unemployment rate between t and $t+k$.[50] I assume $h = 3$ quarters and $k = 2$ quarters, roughly in accordance with evidence from VAR analysis, cf. Christiano et al [2001]. I initialize the priors using the post-Volcker observations. The estimation is based on 10,000 runs of the Gibbs Sampler, discarding the first 2,000 to allow for convergence to the ergodic distribution.

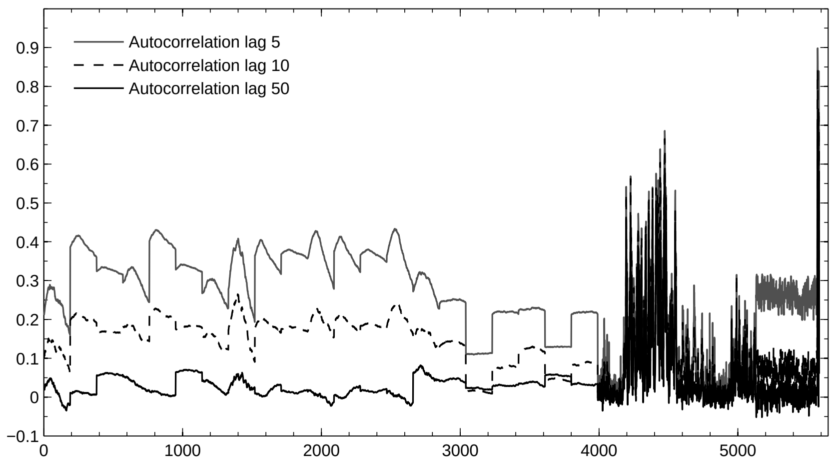
Figure 5.1 present the activism estimates, α_t^{π} and α_t^{u}. Across the overlapping sample, the pattern of time-variation in Figure 5.1 resembles reasonably closely the estimates discussed in Figure 3.2: both the level and the changes in the two estimates of $\alpha_t^{\pi,m}$ and $\alpha_t^{u,m}$ roughly coincide for all periods. In fact, the estimates are

[49]Note that the Greenbook forecasts are not available at standard frequencies: usually there are only eight meetings per year (prior to 1976 there were, however, monthly meetings). All data is sampled for the months that have Greenbook forecasts.

[50]I again use the three month TBILL rate as my preferred measure of the policy rate.

never statistically different from each other. That said, there are some differences in the median estimates; in particular in the mid-1980s for unemployment activism. This divergence could potentially indicate either: (a) a short-coming in the VAR-approach to approximate the structural equations governing the economy in that period; or (b), that the potential endogeneity and "quirks" in the real-time data contaminate the estimates relatively more in the mid-1980s. Comparing estimates along the same sample path, the probability that α_t^{π} increased in between 1977 (under the chairmanship of Burns) and 1980 (under Volcker) is 0.99, as compared to 0.96 previously; i.e., there remains strong evidence in favor of a shift in policy activism between the two dates. Above all though, the fact that these results using "exogenous" expectations corroborate to such an extent with the earlier findings reaffirms the conclusions of Section 3.

FIGURE 5.2. Autocorrelation of draws



Autocorrelation coefficients at lag 5, 10 and 50. The ordering of the variables is described in the main text.

APPENDIX C: CONVERGENCE DIAGNOSTICS OF THE GIBBS SAMPLER ALGORITHM

This appendix evaluates the convergence of the Gibbs Sampler Algorithm in the baseline scenario.[51]

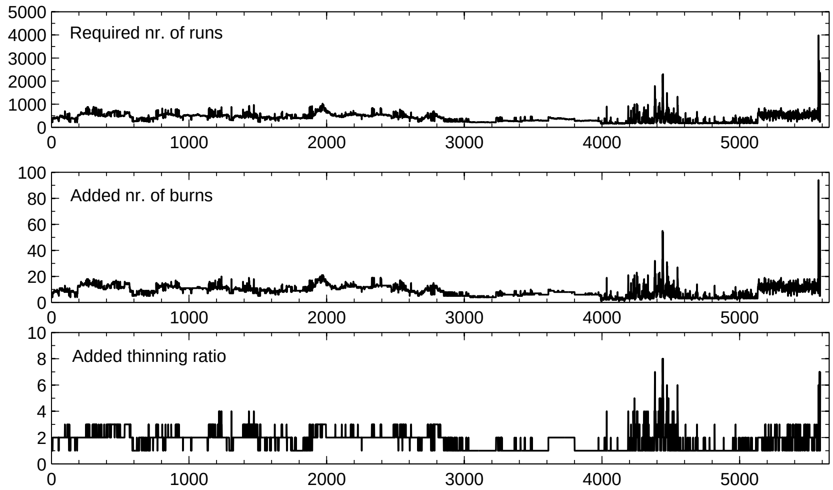
To judge how well the Markov Chain mixes, Figure 5.2 shows the autocorrelation coefficient at lags 5, 10 and 50 for all model parameters. I order the 11,970 $\mathbf{A_t}$ parameters first; the 1,710 $\mathbf{a_t}$ and $\log(\mathbf{h_t})$ second and third, respectively; and finally, the 455 hyperparameters in $\mathbf{V}$ fourth. A high degree of autocorrelation indicates a need to carry out more draws to achieve a sample of sufficient size to draw accurate inference on posterior parameters. As Figure 5.2 shows, the autocorrelations decay fairly quickly and at lag 10 remain below 0.2 for the vast majority of the parameters.

Closely related, Figure 5.3 plots (in the same order) the set of Rafetery and Lewis [1995] convergence diagnostics assessing: (1) the minimum number of draws required to achieve a desired degree of precision in the estimation of the posterior distribution; (2) the added amount of burns required to achieve a stationary distribution and (3), the added amount of thinning required to achieve a roughly independent sample. I use a standard specification with q, the quantile of interest, equal to 0.025*;* r, the desired degree of accuracy in the estimated quantiles, equal to 0.025; and finally, s, the minimum probability of achieving the accuracy goal equal to 0.95. As Figure 5.2 shows, the required number of draws in each case remains well below the total number of draws conducted in the baseline scenario. In addition, the suggested added number of burns is small and the thinning ratio averages around 2.0, consistent with the relative fast decay of the autocorrelations.

As a final convergence check, I calculate the Inefficiency Factors [IFs] proposed by Geweke [1991] for the posterior estimates of the distribution of the parameters. The IFs are the inverse of the relative numerical efficiencies (RNEs), which provide an estimate of the ratio of the number of draws that would be required to produce the same numerical accuracy as if the draws presented had been made from an i.i.d sample drawn directly from the posterior distribution. Typically, values below 25 are considered satisfactory. As Table 2 shows, for the vast majority of the parameters this appears to be the case. That said, quite high IFs are visible for

[51]All diagnostics are calculated using the coda function in MATLAB, created by James LeSage.

FIGURE 5.3. Raftery and Lewis' [1995] Converge Diagnostics



Raftery and Lewis' [1995] converge diagnostics for the estimates of the posterior distribution of the parameters. Panel (a) depicts the required number of runs in order to achieve the desired degree of accuracy; Panel (b), the suggested added number of burns to reach the ergodic distribution; and finally, Panel (c), the added degree of thinning required to attain a roughly independent sample. The ordering of the variables is described in the main text.

TABLE 6. Summary Statistics of the Inefficiency Factors

	Median	Mean	Std. dev.	Min.	Max.	10pct.	90pct.
V	19.21	31.85	21.61	0.89	115.82	2.05	64.26
A	15.29	19.94	4.43	6.21	26.55	9.51	22.02
h	5.16	8.65	9.56	1.35	71.74	2.13	19.74
a	6.99	9.61	19.57	2.22	192.23	5.11	9.37

Summary statistics of the inefficiency factors of the posterior distribution of the parameters. A 4% tapered window is used in the estimation of the spectral density at zero frequency. Variables are denoted as in the main text.

some parameters in **V**, however, for all other parameters, 90% of the IFs are below the 25 barrier.

In conclusion, considering the high dimensionality of the model, the converge checks appear satisfactory and the MCMC algorithm appears to obtain the ergodic distribution fairly quickly.

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