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Depression Econometrics: A FAVAR Model of Monetary Policy During The Great Depression

Pooyan Amir Ahmadi
&
Albrecht Ritschl

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Department of Economic History
London School of Economics
Houghton Street
London, WC2A 2AE

Tel: +44 (0) 20 7955 7860
Fax: +44 (0) 20 7955 7730

Depression Econometrics: A FAVAR Model of Monetary Policy During the Great Depression[*]

Pooyan Amir Ahmadi and Albrecht Ritschl

Abstract

The prominent role of monetary policy in the U.S. interwar depression has been conventional wisdom since Friedman and Schwartz [1963]. This paper presents evidence on both the surprise and the systematic components of monetary policy between 1929 and 1933. Doubts surrounding GDP estimates for the 1920s would call into question conventional VAR techniques. We therefore adopt the FAVAR methodology of Bernanke, Boivin, and Eliasz [2005], aggregating a large number of time series into a few factors and inserting these into a monetary policy VAR. We work in a Bayesian framework and apply MCMC methods to obtain the posteriors. Employing the generalized sign restriction approach toward identification of Amir Ahmadi and Uhlig [2008], we find the effects of monetary policy shocks to have been moderate. To analyze the systematic policy component, we back out the monetary policy reaction function and its response to aggregate supply and demand shocks. Results broadly confirm the Friedman/Schwartz view about restrictive monetary policy, but indicate only moderate effects. We further analyze systematic policy through conditional forecasts of key time series at critical junctures, taken with and without the policy instrument. Effects are again quite moderate. Our results caution against a predominantly monetary interpretation of the Great Depression.

1. Introduction

Beginning with the seminal contribution of Friedman and Schwartz [1963], the Great Depression has traditionally been associated with restrictive monetary policy. In 1928, the Federal Reserve Bank of New York, then the leading institution in U.S. monetary policy, responded to

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Contact: amir@wiwi.hu-berlin.de; a.o.ritschl@lse.ac.uk.

the stock market boom with interest rate hikes from 3.5 % in January to 5 % in September. Between July and October of 1929, it raised its discount rate by another percentage point. After the October stock market crash, the discount rate was reduced in several steps to reach 1.5 % in June 1931. However, given the rapid decline in price levels, ex-post real interest rates remained high. Monetary authorities also failed to intervene in the banking crisis that unfolded beginning in December of 1930, and interest rates increased again after Britain’s departure from the Gold Standard in October, 1931.

This paper is about submitting the role of monetary policy in the Great Depression hypothesis to empirical test. This task is a complex one, as several different channels of monetary policy transmission during the depression have been proposed. The strongest form of the paradigm, expounded by Schwartz [1981], states that both the initial recessionary impulse and the later deepening of the recession were largely caused by the Federal Reserve. The original position of Friedman and Schwartz [1963] centred more strongly on the role of monetary policy in deepening the slump. This weaker version of the monetary paradigm is also consistent with the emphasis placed on bank panics by Bernanke [1983,1985] and others. Bernanke’s research focused on financial channels of monetary policy transmission, emphasizing the role of information asymmetries and participation constraints in debtor/creditor relations, as well as of debt deflation. Bernanke and Carey [1996] also looked at nominal wage stickiness as an alternative mechanism of monetary policy transmission during the depression.

In the light of these various proposed transmission mechanisms, traditional VAR analysis soon reaches its limits, as it only allows for a small number of time series to model the pertinent dynamics of the money/income causation. One alternative that has been pursued in the recent literature was to obtain counterfactuals from well-specified DSGE models of the Great Depression that focus on one specific monetary transmission mechanism. Bordo, Erceg, and Evans [2000] specify a DSGE model with sticky wages, finding evidence in favour of a nominal wage rigidity channel of monetary policy transmission. Christiano, Motto and Rostagno [2003] propose a DSGE model with a permanent increase in liquidity preference during the depression, and argue that given this preference shift, easy monetary policy a la Friedman and Schwartz would have mitigated most of the slump.

However, non-monetary interpretations using DSGE techniques seem to have worked equally well in modelling the interwar depression. Cole and Ohanian [2005] specified a model of collective wage bargaining to argue that real wage rigidity under the New Deal prevented a more complete recovery from the depression after 1933. Combining monopolistic competition in product markets with search frictions in the labor market, Ebell and Ritschl [2007] argued that the Great Depression could be viewed as an equilibrium shift, induced by high wage policies under the Hoover administration. In a model of international business cycle transmission in the Great Depression, Cole, Ohanian, and Leung [2005] examined monetary policy and productivity shocks alongside each other, and found only a minor role for monetary shocks in explaining the slump. Chari, Kehoe and McGrattan [2007] modelled the Great Depression using a neoclassical business cycle accounting framework with frictions. On the other extreme of the spectrum of non-monetary models, Harrison and Weder [2005] calibrate a sunspot model of investor behaviour, which finds strong evidence for an investment-led downturn that was unrelated to monetary policy. Hence, existing research offers a whole menu of interpretations which all seem consistent with the data, although they partly exclude each other.

This is what motivates the approach taken in the present paper. Compared to existing research on the Great Depression, we aim to impose less structure and at the same time analyze a richer dataset. We start out from parsimonious yet informative prior assumptions on the effects of monetary policy. We gear our estimation toward exploiting the information on the common components of business cycle movements in a large cross section of time series. To this end, we employ the factor-augmented vector autoregression (FAVAR) techniques introduced into monetary policy by, among others, Bernanke and Boivin [2003], Stock and Watson [2005] and Bernanke, Boivin, and Eliasz [2005] (henceforth BBE). The idea behind this can be interpreted as augmenting the information content in a VAR by a two-step procedure. In a first step, the common dynamics in a large panel of time series are identified using dynamic factor model (DFM) techniques as developed by Geweke [1977] and Sims and Sargent [1977]. In a second step, the causality between a properly chosen policy instrument and some representative measure of economic activity is examined in a traditional VAR, including the factors as the relevant description of the underlying economic dynamics. Estimation is either in two steps, employing principal-component techniques for DFM part and Maximum Likelihood for the FAVAR, or simultaneous by Bayesian likelihood methods or suitable numerical approximations. In the present paper, we adhere to the Bayesian approach, which allows us to exploit the information on the observables in the VAR specification more completely.

Both traditional VAR analysis and FAVARs for U.S. data have obtained significant but quantitatively small effects of monetary policy on output. In a long-term study on the U.S. since the 1930s, Sims [1999] finds that monetary policy on average explains around 12 % of forecast error variance in output. Using the FAVAR technique, Amir Ahmadi and Uhlig [2008] report a variance explanation of less than 14 % for industrial output and roughly 10 % for unemployment, order flows, and capacity utilization, evaluated at a 48-months horizon.

VAR evidence on the Great Depression is sparse. Ritschl and Woitek [2000] employ time-varying techniques on four different specifications of the monetary transmission mechanism and find that monetary policy explains less than 5 % of output forecast error variance. They also find the forecasting performance of their VARs to be poor. This suggests that a traditional monetary policy VAR, run with the imperfect aggregate data available for the interwar period, might not be able to capture the business cycle dynamics of the Great Depression very well. Given the limitations to data quality in the interwar period, working in a FAVAR framework thus seems particularly promising, as the underlying DFM aggregates information included in a large panel of disaggregate time series. The statistical aggregation procedure implicit in the FAVAR presents an alternative to historical monetary statistics and reconstructed national accounts with their unavoidable interpolations and inaccuracies.

The aim of the present paper is to track the effects of U.S. monetary policy during the interwar years in the data-rich environment provided by the FAVAR approach, and to evaluate them against the post-war evidence collected in previous studies. The Friedman/Schwartz [1963] hypothesis on the monetary causes of the Great Depression would suggest that the effects of interwar monetary policy were significant and certainly larger than the rather modest estimates obtained for post-war U.S. data. Any findings that suggest only minor effects of monetary policy would then have to be interpreted as cautioning against a primarily monetary explanation of the Great Depression.

The task at hand is a double one. On the one hand, we follow the standard approach to policy analysis in a VAR, calculating impulse response sequences and forecast error variance decompositions under identifying assumptions about the correlation structure of the VAR residuals. The implicit assumption behind this approach is the neutrality of anticipated monetary policy changes, i.e. of movements along the central bank's reaction function. On the other, we also attempt to trace possible systematic effects of monetary policy, which would be present under a wider set of frictions that allow for (however short-lived) deviations from non-neutrality of movements along the monetary policy reaction function itself. In a VAR, such systematic effects would be identified through Granger causality of monetary policy for other variables of interest. We implement this by taking Bayesian forecasts of key economic indicators from FAVARs with and without past realizations of the policy instrument. Improvements of the forecast in the presence of the policy instrument relative to the baseline would then be an indication of possible systematic policy effects, while the sign of the correction would indicate the expansionary or recessionary stance of systematic policy. This is the closest we can get to providing a test of monetary policy effects in the spirit of Friedman and Schwartz' [1963] hypothesis. Furthermore we identify the reaction of different policy instruments to aggregate supply and demand shocks tracing the systematic reaction of the monetary authority to changes in the economy.

We proceed in several steps. Section (2) presents the basic econometric framework, which closely follows the Bayesian version of BBE's FAVAR model. Section (3) describes the estimation procedure and Section (4) discusses the model fit. Section (5) provides results for the stochastic component of monetary policy empirical results for policy, obtaining shocks from the generalized sign restriction identification approach described in Amir Ahmadi and Uhlig [2008]. Section (6) analyzes the policy reaction to identified aggregate supply and demand shocks. Section (7) looks at possible effects of systematic monetary policy, examining conditional forecasts of key time series with and without the policy instrument at critical junctures. Section (8) concludes.

2. The Model

The key idea behind dynamic factor models is to parsimoniously represent the co-movements in a large set of cross-sectional data by only a limited number of unobserved latent factors .The dynamic factor model (henceforth DFM) allows dynamics in both the common component - represented by these factors and their respective factor loadings - and the variable-specific idiosyncratic component. The factor-augmented vector autoregression (henceforth FAVAR) model is a hybrid between a DFM and the standard structural VAR model: a joint VAR is specified for some series of interest f_t^{y} and some factors f_t^{c} that are extracted from a large panel of informational time series X_t^{c}. The working hypothesis of the FAVAR model is that while a narrow set of variables f_t^{y}, notably the policy instrument of the central bank, are perfectly observable and have pervasive effects on the economy, the underlying dynamics of the economy are less perfectly observable, and hence a VAR in just a few key variables would potentially suffer from omitted variable bias. As increasing the size of a VAR is impractical due to problems of dimensionality, the FAVAR approach aims to extract the common dynamics from a wide set of informational indicator series X_t^{c}, and to include these in the VAR, represented by a small number of factors f_t^{c} This approach is well suited for structural analysis such as impulse response analysis and variance decomposition (in particular for the problem at hand). For the estimation procedure the model has to be cast in a state-space representation. The informational variables X_t^{c} included in the observation equation are assumed to be driven by observable variables with pervasive effects on the economy (e.g. the central bank's policy instrument), f_t^{y}, a small number of unobservable common factors,

f_t^c, which together represent the main "driving forces" of the economy, and an idiosyncratic component e_t^c, i.e

(2.1) $$X_t^c = \lambda^c f_t^c + \lambda^y f_t^y + e_t^c$$

(2.2) $$e_t^c \sim N(0, R_e)$$

Here λ^f and λ^Y denote the matrix of factor loadings of the factors and the policy instrument with dimension $[N_c \times K_c]$ and $[N_c \times K_Y]$ respectively. The error term e_t^c has mean 0 and covariance R, which is assumed to be diagonal. Hence the error terms of the observable variables are mutually uncorrelated. The FAVAR state equation represents the joint dynamics of factors and the observable policy variables (f_t^c, f_t)

(2.3) $$\begin{bmatrix} f_t^c \\ f_t^y \end{bmatrix} = b(L) \begin{bmatrix} f_{t-1}^c \\ f_{t-1}^y \end{bmatrix} + Av_t^f$$

(2.4) $$u_t^f = Av_t^f$$

(2.5) $$u_t^f \sim N(0, Q_u)$$

where u_t^f is the time t reduced form shock and v_t^f the time t structural shock, with the contemporaneous relations represented through matrix A. The dimensions are $[K \times 1]$, $[K \times 1]$ and $[K \times K]$ respectively, where $K = K_c + N_y$ denotes the total number of factors including the perfectly observables ones. In the subsequent estimation we consider the following finite order VAR(P) approximation of the unobserved state dynamics

(2.6) $$\begin{bmatrix} f_t^c \\ f_t^y \end{bmatrix} = \sum_{p=1}^{P} b_p \begin{bmatrix} f_{t-1}^c \\ f_{t-1}^y \end{bmatrix} + Av_t^f.$$

2.1 Factor Identification

Identification of the model against rotational indeterminacy requires normalization and additional restrictions. We follow the approach of Bernanke, Boivin and Eliasz [2005] and normalize the upper $[K_c \times K_c]$ block of λ^f to the identity matrix and restrict the upper $[K_c \times N_y]$ block of λ^y to only contain zeros.[1]

3. Estimation and Identification of Shocks

3.1 Estimation

We cast the state space model of the previous section into a stacked first order Markov state space representation. Estimation is facilitated via a multi-move Gibbs sampler which involves the Kalman smoother for evaluating the likelihood of the unobserved factors. Given the sequence of sampled factors we draw the parameters via posterior sampling. In particular we employ a Gibbs sampler for the two blocks of parameters, the first referring to the parameters of the observation equation and the second block contains the parameter space of the state equation. The above state space representation can be rewritten as

$$X_t = \lambda f_t + e_t \tag{3.1}$$

$$f_t = \sum_{p=1}^{P} b_p f_{t-p} + u_t^f \tag{3.2}$$

where

[1] Note that this approach is over-identified. However, it is easy to implement and does not require further sign restrictions on the factor loadings or further normalizations of the covariance matrices of the residuals. Alternative restrictions and normalization for the factor identification are reported e.g. in Geweke and Zhou [1996]. The analysis and comparison of the different approaches to factor identification goes beyond the scope of this paper.

$$(3.3) \qquad \lambda = \begin{bmatrix} \lambda^f & \lambda^y \\ 0_{N_y \times K_c} & I_{N_y} \end{bmatrix}, \quad R = \begin{bmatrix} R_e & 0 \\ 0 & 0 \end{bmatrix}$$

where $X_t = (X_t^{c\,/}, f_t^{y\,/})^/, e_t^/ = (e_t^{c\,/}\, 0)^/$ and $f_t = (f_t^{c\,/}, f_t^{y\,/})^{\,/}$. For the companion form of the model we define

$F_t = (f_t^{\,/}, f_{t-1}^{\,/}, \ldots, f_{t-p+1}^{\,/})^{\,/}, u_t = (u_t^{f^/}, 0, \ldots, 0)^/$, $b = (b_1, b_2, \ldots, b_p)$ and

$$B = \begin{bmatrix} b_1 & b_2 & \ldots & b_{p-1} & b_p \\ I_K & 0 & \ldots & 0 & 0 \\ 0 & I_K & \ldots & 0 & 0 \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ 0 & 0 & \ldots & I_K & 0 \end{bmatrix}, \quad Q = \begin{bmatrix} Q_u & 0 & \ldots & 0 \\ 0 & 0 & \ldots & 0 \\ \ldots & \ldots & \ldots & \ldots \\ 0 & 0 & \ldots & 0 \end{bmatrix}.$$

where the 0's and Q have dimension $[K \times K]$ and $[PK \times PK]$ respectively. We define $\Lambda \equiv [\,\lambda\; 0 \ldots 0\,]$. The final companion form results in

$$\begin{aligned} &(3.4) \qquad & F_t &= BF_{t-1} + u_t \\ &(3.5) \qquad & X_t &= \Lambda F_t + e_t \end{aligned}$$

The parameter space to be estimated is given by $\theta = (\lambda^y, \lambda^f, b, R_e, Q_u)$ and the history of the observed data and the latent factors is given by $X^T = (X_1, \ldots, X_T)$ and $F^T = (F_1, \ldots, F_T)$ respectively. Hence the estimation algorithm can be simplified and summarized by two steps relying on the blocking scheme. First we initialize the sampler by finding starting values $\theta^0 = (\lambda^{f0}, \lambda^{y0}, b^0, R_e^0, Q_u^0)$ and (F^0) Given a set of initial values (θ^0, F^0) we sample the parameters conditional on the data, and afterwards sample the latent factors given the new set of parameters and data.

Step 1: $F^{T(g)} = p(F^T \mid X^T, \theta^{(g-1)})$

Step 2: $\theta^{(g)} = p(\theta \mid X^T, F^{T(g)})$

we cycle through this procedure sufficiently many times until the target distribution has been empirically approximated. An initial number of draws will be discarded as burn in. To reduce the dependency of the posterior sampler and to reduce the autocorrelation of the chain a thinning parameter $\kappa \geq 1$ is introduced. Hence only every κ^{th} draw after the burn in is stored. Details about the implementation and specification are reported in section (4) on the empirical application. Algorithm (1) contains a pseudo code of the employed algorithm for illustrative purposes. A detailed technical derivation and description of the posterior sampling technique can be found in appendix (A).

Algorithm 1 FAVAR estimation via Multi-move Gibbs sampling

Step 0, [Initialization]: $p_0(F^0, \lambda^{f0}, \lambda^{y0}, b^0, R_e^0, Q_u^0)$.

```
    Set g ⇝ 0.
     Get initial values for states and parameters.
    Set g ⇝ 1.
```

Step 1, [Evaluate likelihood of latent states]: $p(F^T \mid X^T, \lambda, R_e, b, Q_u) \sim FFBS$

```
     Do forward filtering and backward sampling
```

Step 2, [Sample parameters from observation equation]: $p(\lambda_n, R_{e,nn} \mid X^T, F^T)$

$2.a: \quad p(R_{e,nn} \mid \lambda_n^{(g-1)}, X^T, F^T) \sim f_{\mathcal{IG}}$

$2.b: \quad p(\lambda_n \mid R_{e,nn}^{(g)}, X^T, F^T) \sim f_{\mathcal{N}}$

```
     Sample equation by equation due to conditional Gaussianity.
```

Step 3, [Sample parameters from state equation]: $p(b, Q_u \mid X^T, F^T)$

$3.a: \quad p(Q_u \mid F^{T(g)}, X^T) \sim f_{\mathcal{IW}}$

$3.b: \quad p(b \mid Q_u^{(g)}, F^{T(g)}, X^T) \sim f_{\mathcal{N}}$

```
     Sample parameters from a normal inverted Wishart density.
   If g ≤ G set g ⇝ g+1 and go to Step 1. Otherwise stop.
```

3.2 Identification of Shocks

One objective of this paper is to analyze the role of monetary policy shocks during the interwar US Great Depression. This involves identifying the non-systematic part of monetary policy. The traditional approach in our model framework would be the Cholesky identification, where the policy instrument is ordered last in the FAVAR equation. Then, the policy instrument reacts contemporaneously to the other variables through the common factors but not vice versa. As shown in Amir Ahmadi and Uhlig [2008] this approach is flawed and produces unreasonable results for post-war US data[2]. In this paper we therefore follow the methodology of Amir Ahmadi and Uhlig [2008]. Generalizing results of Uhlig [2005] to the dynamic factor model, this approach identifies policy through restrictions on the sign of the impulse response functions for specified periods.[3]

Identification of structural shocks through imposing sign restrictions is based on assumptions about the sign of the impulse response functions of key macroeconomic variables. Such restrictions should represent ‘conventional wisdom’ derived from economic theory that most researchers can agree on[4]. Sign restrictions turn out to be particularly well suited to the FAVAR model, as they are straightforward to impose on a large number of series.

The structural FAVAR is obtained by inserting (2.4) into the reduced form version in (3.2):

$$f_t = \sum_{p=1}^{P} b_p f_{t-p} + A v_t^f$$

The crucial step is to represent the one-step ahead prediction error v_t^f as a linear combination of suitably defined orthogonalized structural shocks (see Uhlig [2005]. For this, assume the fundamental innovations are mutually independent and have unit variance,

$$E[v_t^f v_t^{f'}] = I_K$$

[2] We also experimented with the traditional Cholesky decomposition, and encountered similar problems on an even larger scale.
[3] Implementations of signs restrictions in similar models can also be found e.g. in Mönch [2005] and Rubio-Ramirez, Waggoner and Zha [2007].
[4] The sign restriction approach which was introduced to the SVAR literature by Dywer [1997], Faust [1998], Canova and de Nicolo [2002], and Uhlig [2005].

The restriction on A then emerges from the covariance structure of the reduced form factor innovation, which leads to:

$$
\begin{aligned}
Q_u &= E[u_t^f u_t^{f\prime}] \\
E[u_t^f u_t^{f\prime}] &= AE[v_t^f v_t^{f\prime}]A' \\
AE[v_t^f v_t^{f\prime}]A' &= AA'
\end{aligned}
$$

Following Uhlig [2005] we define an impulse vector as a column of matrix A. Such a vector can be obtained from any decomposition, e.g. the Cholesky decomposition, of the VCV matrix of the factor residual matrix ĀĀ' = Q_u

***Definition 1** The vector $a \in \Re^K$ is called an impulse vector, if there is some matrix A, so that $AA' = Q_u$ and so that a is a column of A*

According to Proposition 1 of Uhlig [2005,pp. 18], any impulse vector can be characterized as follows. Let ĀĀ' = Q_u be the Cholesky decomposition. Then a is an impulse vector if and only if there is some $K-$dimensional vector α of unit length so that $a = \bar{A}\alpha$. Given the impulse vector, let $r_k(s) \in \Re^K$ be the vector response at horizon s to the k-th shock in a Cholesky decomposition of Q_u Then the impulse response $r_a(s)$ for a is simply given by

$$
r_a(s) = \sum_{i=1}^{K} \alpha_i r_i(s).
$$

For estimation consider the companion form of the state space in (3.4)-(3.5)

$$
\begin{aligned}
F_t &= BF_{t-1} + u_t \\
X_t &= \Lambda F_t + e_t
\end{aligned}
$$

To compute the impulse response vector a let $\mathbf{a} = [a', 0_{1,K(P-1)}]'$ and compute

$$r_{a,k}(s) \;=\; (B^s \mathbf{a})_k.$$

to get the impulse response of factor k to an impulse in a at horizon s. Note that $r_a(s)$ is the vector of impulse response functions of all factors to an impulse vector a at horizon s. As a second step we have to compute the impulse response functions of the single variables by combining the respective factor loading with $r_a(s)$ accordingly. This requires us to compute

$$r_a^n(s) \;=\; \Lambda_n r_a(s).$$

where Λ_n is the respective n-th row vector of the factor loading matrix. We set the sign restriction on the shape of the individual impulse response functions according to the following assumption:

Assumption 1 A (contractionary) monetary policy impulse vector *is an impulse vector a so that the individual impulse response functions to a of price and non-borrowed reserves are not positive and the impulse responses for the policy instrument such as the short term discount rate (controllable monetary aggregate, e.g. M1) is not negative (positive), for a specified horizon* $s = 0, \ldots, S$.

Table (1) provides a summary of the identifying sign restrictions we impose.

Table 1: **Sign restrictions imposed for identification**

	a_{money}	a_{supply}	a_{demand}
CPI Inflation	≤ 0	$0 \geq$	≤ 0
General Price Index	≤ 0	$0 \geq$	≤ 0
Whole Sale Price Index Metal	≤ 0		
FRB Production Index		≤ 0	≤ 0
Discount Rate	$0 \geq$		
Commercial Paper Rate	$0 \geq$		
M0	≤ 0		

This table summarizes the restrictions imposed for the contemporaneous period and the specified number of periods following the shock. Each column defines an impulse vector to one orthogonal shock. The shocks are: a_{money} : deflationary monetary policy shock, a_{demand} negative demand shock, a_{supply} positive supply shock.

4. **Specification and Model Fit**

4.1 Data and Model Specification

All data are taken from the NBER's macroeconomic history database. Most of these data are contemporary and were collected for the business cycle dating project of Burns and Mitchell [1947]. Our dataset includes a total of 164 time series, ranging from industrial production to order flows and housing start-ups, agricultural, raw material, and finished goods prices, measures of deposits, savings, and liquidity in the banking system, as well as interest rates on call money, commercial paper, and various medium and long term bonds. Table 2 in Appendix B provides the details along with the NBER macroeconomic database classification codes. To achieve stationarity, some of the data series were transformed into logarithmic first differences.

We estimate the model using the data in monthly frequency for the US from 1919:02 until 1939:02. This period covers the slide into and recovery from the recession of 1920-21, as well as the downturn of the Great Depression. In the following, we report the results from a FAVAR model with $K_c = 4$ factors and $P = 12$ lags[5] on a dataset including one policy instrument and N=164 informational variables.[6]

4.2 Model Fit

We performed several checks to see whether the model represents the data in an adequate manner. The first obvious check is to obtain the goodness of fit of the observation equation (2.1) for each series X^c Results are listed in Table (3) below. As can be seen, the overall fit is high; the factors seem to capture the common components of the interwar business cycle well. Thus, a VAR in these factors or common components should not suffer from omitted variable bias. This implies that adding individual series to the VAR in eq. (2.3) above will not alter the shape of any impulse response functions substantially.[7] Upon increasing the number of factors, the model fit did not change much, and the subsequent VAR analysis remained basically unaffected.

4.3 Convergence Diagnostics

To ensure that the results are based on converged simulation chains that represent the respective target distribution and not only e.g. some local mode, we applied a battery of further convergence diagnostics for the simulated parameters based on the Gibbs sampler. The respective diagnostics are not a guarantee for convergence but can reduce the uncertainty. The diagnostics we employed are widespread in the MCMC

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[5] We tried several versions with different lag length (up to 13), without much change in the results.

[6] We experimented with including more factors, and found that little information was added by increasing the dimension of the system. This is broadly consistent with the results in Stock and Watson [2005], who report an optimal choice of seven factors for their post-war U.S. data set of 132 series with this methodology.

[7] If this property holds strictly, the factor model is termed exact. If including individual series adds to the information content significantly but with small coefficients, the factor model is approximate. See Stock and Watson [2005] for a survey of the implications and for testing strategies.

literature, and are reported in Appendix D. We also checked the precision of the sampler by plotting the associated error bands. An example for the extracted factors covering the 95 % probability band is given in Figure (1).

5. The Surprise Component of Monetary Policy

We follow standard procedure in VAR analysis and obtain impulse responses to identified monetary policy shocks, employing the FAVAR model as a representation of the monetary transmission mechanism. As mentioned above, our attempts to obtain economically meaningful impulse responses from a Cholesky decomposition of the FAVAR model failed[8]. Hence we resort to Uhlig's [2005] sign restriction strategy. We implement this by imposing, among others, a sign restriction on the response of the CPI to a contractionary monetary shock[9].

There has been some uncertainty as to which monetary policy instrument was actually used at the time. The discussions in Friedman and Schwartz [1963] suggest a role for targeting monetary aggregates, but also leave a role for interest rates. We present results for five model specifications corresponding to candidate policy instruments. These include two interest rates – the Federal Discount Rate and the rate on prime commercial paper – and three monetary aggregates – high powered money M0, as well as M1 and M2.

In spite of the restrictions we impose, the results are not encouraging. The responses of the FRB index of manufacturing to a contractionary interest rate shock in the Discount Rate model follow a rotated S-shaped pattern, being near-significantly negative both at the one year and after the three year lag, and weakly positive in between (see Figure 4 below). The contribution of a contractionary discount rate

[8] Results are available upon request.
[9] A detailed list of sign restrictions imposed for identification can be found in table (1)

policy shock to the forecast error variance of industrial production remains below 10 % over four years (see Table 4 for a tabulation of all variance decompositions reported here). Choosing the Commercial Paper Rate as the relevant policy instrument instead, the impulse response function remains in negative territory throughout (see Figure 5). However, the values are insignificant, and the contribution of the policy shock to the forecast error variance of FRB manufacturing remains solidly below 10 %. This is pretty much what Uhlig [2005] found for U.S. postwar data.

Model specifications with monetary aggregates as the policy instrument fare slightly better. Responses to a shock in high-powered money M0 as the policy instrument are again S-shaped, veering from negative into positive and back into negative (Figure 6). The same S-shaped pattern is obtained for responses to shocks in M2, except that the response in the second year goes to zero instead of into positive (Figure 8). Responses to shocks in M1 look well behaved for the first year but then rapidly lose force (Figure 7). The variance decompositions show that responses to M0 and M1 shocks contributed between 15 and 20 % to the forecast error variance of FRB manufacturing output. For M2 as the policy instrument, the explained variance of FRB manufacturing remains well below 10 %, averaging between 6 and 7 % over the four-year horizon that we look at. This seems close to the values reported by BBE [2005] for postwar industrial output.[10]

Drawing the results of this section together, we find that the responses of the real economy to contractionary monetary shocks are in generally weak and, pathologically, change their signs. This result obtains under four of five different specifications of the monetary policy instrument and two different identification schemes for the innovations in the VAR. Still the best results we obtain for responses to shocks in M1, which do

[10] A full set of impulse response functions for all series of the dataset is available from the authors upon request.

not exhibit sign changes and which explain around 20 % of the forecast error variance of manufacturing output. This is in line with postwar data. A FAVAR model drawing on rich data from the interwar period does not find evidence for unusual, pervasive negative effects of contractionary monetary policy during the Great Depression.

6. The Systematic Component of Monetary Policy

6.1 The Policy Reaction Function

Our analysis so far has been agnostic about the choice of monetary policy instruments, and has worked with several candidate policy instruments instead. This section attempts to identify the reaction function of monetary policy during the Great Depression. To this end, we obtain the responses of the respective candidate monetary policy instrument to aggregate demand and supply shocks, using the same techniques as before. In this way, we can directly measure if and how the monetary authority reacted to change in output and prices.

6.2 Aggregate Supply Shocks

6.2.1 Full Sample Analysis

As laid out before, we again employ a sign restrictions approach to identify supply and demand shocks. We identify a positive aggregate supply shock by restricting the response of CPI inflation to be negative and the response of the FRB index of manufacturing to be positive for a horizon of 6 months. Results indicate only weak systematic responses. For the observation period as a whole, the instruments in the Commercial Paper Rate model (Figure 9) and Federal Discount Rate models (Figure 10) exhibit moves in the wrong direction, with no visible effect on high powered money M0 or on M1. In the Federal Discount Rate model, M2 would even increase significantly, indicating monetary accommodation of the positive supply shock. The monetary targeting models fare slightly better: with M0 or M1 as the monetary instrument (in Figures 11 and 12, respectively), there is a clear-cut negative response of M2 to the positive supply shock. However, there is no clear response of the respective candidate monetary instrument themselves, casting doubt on the underlying money multiplier mechanism. Assuming instead that M2 itself is the monetary instrument (in Figure 13), we do obtain strong interest rate responses, however the response of M2 itself veers into positive after just a few months.

On the basis of these results, it would seem safe to exclude inflation targeting through interest rates from the list of possible policy functions of the Federal Reserve. In principle, the better performance of the monetary specifications provides some support for the Friedman and Schwartz [1963] monetary targeting view. However, the connection between the M0 or M1 and the monetary M2 target seems less than clear-cut, and the responses of M2 are plagued by sign problems. Looking at the observation period as a whole, the evidence for systematic responses of monetary policy seems rather mixed.

6.2.2 Subsample Analysis

Turning to the analysis of subsample periods we find that a somewhat different picture emerges. The subsamples are five critical junctures during the observation period. The first includes the information in the FAVAR as of September 1929, the last month before the New York stock market crash. The second includes all data until November 1930, the last month before the first wave of banking panics. The third extends to June 1931, just before the German debt and reparations moratorium, which triggered Britain's departure from the Gold Standard. The fourth extends to August 1931, the last month before Britain indeed broke away from the Gold Standard. The last is based on information up until

February 1933, the month before Roosevelt's bank closure and the formal inception of the New Deal. For the Federal Discount Rate model, we find an increase in short term interest rates in response to a positive supply shock for up to 2 years. Turning to the three monetary aggregate models, there is now a clear-cut response of the short term interest rates for all sub-periods except for the first one.

The results from the subsample analysis suggests that systematic monetary policy did respond increasingly to supply shocks. The responses of the policy instruments were feeble until 1929 but become more pronounced as time progressed and the slump deepened. Still, the responses we observe are not free of sign problems, indicating that the identifying restrictions may still not be strong enough. Results for all subperiods are provided in Appendix E, available upon request from the authors.

6.3 Aggregate Demand Shocks

6.3.1 Full Sample Analysis

As outlined above, we identify a negative demand shock through imposing a negative response of both FRB manufacturing output and CPI inflation for 6 months. For the full observation period, the response of the policy instruments to a negative aggregate demand shock is insignificant. Assuming an interest rate to be the policy instrument, short term interest rates slightly decrease following a negative demand shock. However, this holds only with a high degree of uncertainty. The specifications with monetary aggregates as instruments perform poorly, indicating no monetary response at all or even a slight degree of accommodation, as in the case of the M1 model. Results are reported in Appendix D in Figures 14 through 18.

6.3.2 Subsample Analysis

Turning to the subsample analysis, we find that the response of interest rates to an adverse demand shock became more pronounced over time. This result holds for all the five models considered. Again, there are sign problems in the responses of the monetary aggregates. Results for the subsample periods, provided in Appendix E, can be requested from the authors.

7. **Any Effects of Systematic Monetary Policy?**

This section ventures into monetary policy effects that might go beyond mere on-off surprises. Under rational expectations and a minimal set of frictions, as is standard in the surprise Phillips curve paradigm since Lucas [1972], systematic monetary policy along a reaction function should be neutral and have no real effects. Any monetary policy effects beyond one-time surprises would entail deviations from rational expectations, or possibly a tighter set of constraints on the pricing mechanism. Such deviations, e.g. Friedman's [1968] backward-looking adaptive expectations approach, appear to come closest in spirit to the original Friedman and Schwartz [1963] hypothesis.

In a reduced form model like the FAVAR we specified, estimates of the model parameters $\theta = (\lambda^y, \lambda^f, b, R_e, Q_u)$ are obtained conditional on the prevailing monetary policy regime $\{f^m\}_o^t$, where m is the monetary policy instrument. This would render policy evaluation through counterfactual variations of the policy sequence meaningless, Lucas [1976]. The only permissible statement is therefore about the information content of the observed policy sequence, conditional on the agents' information set at time t. Under rational expectations, only the innovations to policy matter. Hence, historical realizations of the monetary policy instrument should not influence agents' expectations about the state of the economy, f^y_{t+s}, i.e.

(7.1) $$E(f^y_{t+s} \,|I_t, \{f^m\}^t_o) = E(f^y_{t+s}\, I_t)$$

In principle, both sides of this equation can be evaluated separately, and their empirical forecasting power be compared. This is the estimation strategy adopted in this section. By standard arguments about reverse causality, higher forecasting precision of the LHS of this equation (i.e, when monetary policy history $\{f^m\}^t_o$ is included) is not sufficient for the presence of systematic policy effects. Rational expectations imply, however, that it is a necessary condition: if upon including past realizations of the monetary policy instrument, no improvement in forecasting power is found, it seems safe to rule out systematic policy effects, as predicted by the rational expectations approach.

In what follows we present forecasts of a few key series conditional on information at time t for five critical junctures during the Great Depression. The first includes the information set as of September 1929, the last month before the New York stock market crash. The second includes the data until November 1930, the last month before the first wave of banking panics. The third extends to June 1931, just before the Austrian/German financial crisis. The fourth extends to August 1931, the last month before Britain broke away from the Gold Standard. The last forecast is based on information up until February 1933, the month before Roosevelt's bank closure and the formal inception of the New Deal. For each of these observation subperiods, we obtain a baseline conditional forecast from the FAVAR model excluding all of the candidate monetary policy instruments. For the same subperiods, we also obtain five more conditional forecasts from the FAVAR, each including one of the five candidate monetary policy instruments. The forecast error variance from these predictions can then be compared to the baseline.

Figure 19 shows the results from the baseline forecasts. As can be seen from the forecasts of both FRB manufacturing output and orders of machinery (a leading indicator of equipment investment), neither the onset of the recession nor its further deepening are very well captured by this non-monetary baseline. The baseline from late 1929 does predict a major deflationary episode, but the forecasts taken at later times all wrongly predict an inflationary correction. These non-monetary FAVARs appear to bear out conventional wisdom about the early phase of the slump, as laid out in Friedman and Schwartz [1963] and Bernanke [1983], or in Temin [1989]: the sharp downturn after 1929 was itself not predictable. They also broadly confirm work of Dominguez, Fair, and Shapiro [1988] who found the depression difficult to predict from non-monetary VARs.

Figures 20 and 21 provide forecasts including the commercial paper rate and the discount rate as policy instruments, respectively. The first group of forecasts underpredicts output at very short intervals, generating scenarios of sharp downward spikes and swift recoveries. The forecasts from the discount rate model, in contrast, overpredict output at short intervals. Both group of forecasts broadly agree on predicting inflation.

Figures 22 and 23 suggest that FAVARs including M0 or M1 are somewhat better at predicting output at short intervals than the interest rate models; they also appear to perform better than the non-monetary baseline. This does not hold true for the M2 model, which does not perform better than the non-monetary baseline. Again, all forecasts agree on predicting imminent inflation at most of the critical junctures of the

Great Depression. A central bank employing any of these forecasts would not have regarded its stance during the Great Depression as deflationary.

Examination of the root mean square forecast errors in Tables 5 to 8 confirms this impression. At all horizons, forecasts of output from the M0 and M1 model outperform the non-monetary baseline. This does not hold for the interest rate specifications as well as the M2 model. Unsurprisingly, inclusion of any of the five candidate policy instruments in the FAVAR outperforms the baseline in predicting CPI inflation. Still, it is remarkable that none of the FAVARs predict the protracted deflationary process witnessed in the Great Depression.

This evidence is again consistent with conventional wisdom, see in particular Hamilton [1987, 1992]. There appears to be no evidence of learning or updating about the deflationary process; the priors in the forecast of CPI appear impossible to overturn. Taking this further, if the FAVAR aggregates the information available to monetary decision makers at the time, their lack of worries about easing monetary policy becomes apparent: given the strongly inflationary signals that monetary policy appeared to be emitting, no further action seemed necessary or even useful. Monetary policy in the conventional sense had lost traction in 1929, and apparently die not regain it before well into the 1930s.

Drawing the evidence from this section together, there is some evidence that past realizations of monetary policy help to improve output forecasts during the depression. This is particularly true for M0 and M1 as candidate policy instruments, which beat the non-monetary baseline forecasts. Systematic monetary policy was perhaps more informative about the state of the U.S. economy during the depression than would be compatible with rational expectations. However, even the forecasts including past realizations of monetary policy are far from satisfactory: monetary policy regimes do not appear to explain the Great Depression.

8. **Conclusion**

Recent research has attempted to increase the explanatory power of vector autoregressions for monetary policy analysis by drawing on the common components in a large panel of time series. In this paper, we employed the factor augmented vector autoregression (FAVAR) methodology of Bernanke, Boivin and Eliasz [2005] to reassess the effects of monetary policy on the U.S. economy during the interwar Great Depression. We use a panel of 164 time series, taken from the macroeconomic history database of the NBER, to provide information on the common component of the U.S. business cycle during the interwar period. We specified FAVARs based on this information set for five different specifications of the monetary policy instrument.

To avoid pervasive price puzzles, we were forced to employ a sign restrictions approach. In spite of the identifying assumptions we make, we find that while monetary policy was clearly not neutral, its effects on the real economy were mixed and changed signs. Also, we find the overall contribution of monetary policy to the variance explanation of real variables to be as low as in the postwar period, if not lower.

We obtained the responses of the various candidate policy instruments to identified demand and supply shocks in order to identify the reaction function of monetary policy. In general we found these responses to be weak; however there is evidence of an increased responsiveness to both real and nominal shocks as the depression deepened. We also tested for deviations from the rational expectations paradigm in order to see if systematic policy effects were present. While there is some evidence of such effects, they are again far from clear-cut and pervasive. At the present stage, we conclude that while monetary policy certainly played some role in the interwar depression, there is only scant support for the traditional hypothesis that the Great Depression was mostly a monetary phenomenon.

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Appendix

A Bayesian Inference based on MCMC

A.1 Inference

Bayesian analysis treats the parameters of the model as random variables. We are interested in inference on the parameter space $\Theta = \left(\Lambda^f, \Lambda^y, R, vec(\Phi), \Sigma_v\right)$ and the factors $\{F_t\}_{t=1}^T$. Multi move Gibbs Sampling alternately samples the parameters θ and the factors F_t, given the data. We use the multi move version of the Gibbs sampler because this approach allows us as, a first step, to estimate the unobserved common components, namely the factors via the Kalman filtering technique conditional on the given hyperparameters, and as a second step calculate the hyperparameters of the model given the factors via the Gibbs sampler in the respective blocking.

Let $\widetilde{X}_T = (X_1, \ldots, X_T)$ and $\widetilde{F}_T = (F_1, \ldots, F_T)$ define the histories of X and F, respectively. The task is to derive the posterior densities which require to empirically approximate the marginal posterior densities of F and Θ:

$$\begin{aligned} p(\widetilde{F}_T) &= \int p(\widetilde{F}_T, \theta) d\Theta \\ p(\Theta) &= \int p(\widetilde{F}_T, \Theta) d\widetilde{F}_T \end{aligned}$$

where

$$p(\widetilde{F}_T, \Theta)$$

is the joint posterior density and the integrals are taken with respect to the supports of Θ and F_T respectively. The procedure applied to obtain the empirical approximation of the posterior distribution is the previously mentioned multi move version of the Gibbs sampling technique by Carter and Kohn [1994] which is also applied by BBE[11].

A.2 Choosing the Starting Values Θ^0

In general one can start the iteration cycle with any arbitrary randomly drawn set of parameters, as the joint and marginal empirical distributions of the generated parameters will converge at an exponential rate to its joint and marginal

[11] For more details see Kim and Nelson [1999], Eliasz [2005] and BBE [2005]

target distributions as $S \rightarrow \infty$. This has been shown by Geman and Geman [1984]. We will try several starting values in order to assure that our model has converged and does not depend on the choice of initial values. We follow the advice of Eliasz [2005] that one should judiciously select the starting values in the framework of large dimensional models. In case of large cross-sections, highly dimensional likelihoods make irregularities more likely. This can reduce the number of draws relevant for convergence and hence saves time, which in a computer-intensive statistical framework is of great relevance. We apply the first step estimates of principal component analysis to select the starting values. Since Gelman and Rubin [1992] have shown that a single chain of the Gibbs sampler might give a "false sense of security ", it has become common practice to try out different starting values, at best from a randomly (over)dispersed set of parameters, and then check the convergence verifying that they lead to similar empirical distributions.

A.3 Conditional density of the factors $\{F_t\}_{t=1}^{T}$ given $\widetilde{X}_T$ and Θ

In this subsection we want to draw from

$$p(\widetilde{F}_T \mid \widetilde{X}_T, \Theta)$$

assuming that the hyperparameters of the parameter space Θ are given, hence we describe Bayesian inference on the dynamic evolution of the factors F_t conditional on X_t for $t = 1, \ldots, T$ and conditional on Θ. The transformations that are required to draw the factors have been done in the previous section. The conditional distribution, from which the state vector is generated, can be expressed as the product of conditional distributions by exploiting the Markov property of state space models in the following way

$$p(\widetilde{F}_T \mid \widetilde{X}_T, \Theta) = p(F_T \mid \widetilde{X}_T, \Theta) \prod_{t=1}^{T-1} p_F(F_t \mid F_{t+1}, \widetilde{X}_T, \Theta)$$

The state space model is linear and Gaussian, hence we have:

$$F_T \mid \widetilde{X}_T, \Theta \sim N(F_{T|T}, P_{T|T}) \tag{A.1}$$

$$F_t \mid F_{t+1} X_T, \Theta \sim N(F_{t|t,F_{t+1}}, P_{t|t,F_{t+1}}) \tag{A.2}$$

with

$$
\begin{array}{llcl}
\text{(A.3)} & F_{T|T} & = & E(F_T \mid \widetilde{X}_T, \Theta) \\
\text{(A.4)} & P_{T|T} & = & Cov(F_T \mid \widetilde{X}_T, \Theta) \\
\text{(A.5)} & F_{t|t,F_{t+1}} & = & E(F_t \mid \widetilde{X}_T, F_{t+1}, \Theta) = E(F_t \mid F_{t+1}, F_{t|t}, \Theta) \\
\text{(A.6)} & P_{t|t,F_{t+1}} & = & Cov(F_t \mid \widetilde{X}_T, F_{t+1}, \Theta) = Cov(F_t \mid F_{t+1}, F_{t|t}, \Theta)
\end{array}
$$

where (A.1) holds for the Kalman filter for $t = 1, \ldots, T$ and (A.2) holds for the Kalman smoother for $t = T-1, T-2, \ldots, 1$. Here $F_{t|t}$ refers to the expectation of F_t conditional on information dated t or earlier. We can, then, obtain $F_{t|t}$ and $P_{t|t}$ for $t = 1, \ldots, T$ by the Kalman Filter, conditional on Θ and the data $\widetilde{X}_T$, by applying the formulas in Hamilton (1994), for example. From the last iteration, we obtain $F_{T|T}$ and $P_{T|T}$ and using those, we can draw F_t. We can go backwards through the sample, deriving $F_{T-1|T-1,F_t}$ and $P_{T-1|T-1,F_t}$ by Kalman Filter, drawing F_{T-1} from (14), and so on for F_t, $t = T-2, T-3, \ldots, 1$. A modification of the Kalman filter procedure, as described in Kim and Nelson (1999), is necessary when the number of lags p in the FAVAR equation is greater than 1.

A.4 B.1.3 Conditional density of the parameters Θ given $\widetilde{X}_T$ and $\{F_t\}_{t=1}^T$

Drawing from the conditional distribution of the parameters $p(\Theta \mid \widetilde{X}_T, \widetilde{F}_T)$ can be blocked into to parts, namely the one referring to the observation equation and the second part referring to the state equation.

A.4.1 Conditional density of Λ and R

This part refers to observation equation of the state space model which, conditional on the estimated factors and the data, specifies the distribution of Λ and R. Here we can apply equation by equation OLS in order to obtain $\hat{\Lambda}$ and $\hat{Z}$. This is feasible due to the fact that the errors are uncorrelated. According to the specification by BBE we also assume a proper (conjugate) but diffuse inverse Gamma prior for each σ_n^2:

$$R_{ii}^{prior} \sim \mathcal{IG}(3, 0.001)$$

Note that R is assumed to be diagonal. The posterior then has the following form

$$R_{ii}^{posterior} \mid X_T, F_T \sim \mathcal{IG}(\bar{R}_{ii}, T + 0.001)$$

where $\bar{R}_{ii} = 3 + \hat{Z}_i'\hat{Z}_i + \hat{\Lambda}_i'[M_0^{-1} + (F_T^{(i)'} F_T^{(i)})^{-1}]^{-1}\hat{\Lambda}_i$ and M_0^{-1} denoting the variance parameter in the prior on the coefficients of the i-th equation of Λ_i. The normalization discussed in section (4) in order to identify the factors and the loadings separately requires to set $M_0 = I$. Conditional on the drawn value of R_{ii} the prior on the factor loadings of the i-th equation is:

$$\Lambda_i^{prior} \sim \mathcal{N}(0, R_{ii}M_0^{-1}).$$

The regressors of the i-th equation are represented by $\tilde{\mathbf{F}}_T^{(i)}$. The values of Λ_i are drawn from the posterior

$$\Lambda_i^{posterior} \sim \mathcal{N}(\bar{\Lambda}_i, R_{ii}\bar{M}_i^{-1})$$

where $\bar{\Lambda}_i = \bar{M}_i^{-1}(F_T^{(i)'} F_T^i)\hat{\Lambda}_i$ and $\bar{M}_i^{-1}(F_T^{(i)'} F_T^i)$.

A.4.2 B.1.3.2 Conditional density of $vec(\Phi)$ and Σ_ν

The next Gibbs block requires to draw $vec(\Phi)$ and Σ_ν conditional on the most current draws of the factors, the $R_{ii}'s$ and $\Lambda_i's$ and the data. As the FAVAR equation has a standard VAR form one can likewise estimate $vec(\hat{\Phi})$ and $\hat{\Sigma_\nu}$ via equation by equation OLS. We impose a diffuse conjugate Normal-Wishart prior:

$$\begin{aligned} vec(\Phi)^{prior} \mid \Sigma_\nu &\sim \mathcal{N}(0, \Sigma_\nu \otimes \Omega_0) \\ \Sigma_\nu^{prior} &\sim \mathcal{IW}(\Sigma_{\nu,0}, K + M + 2) \end{aligned}$$

which results in the following posterior:

$$\begin{aligned} vec(\Phi)^{posterior} &\sim \mathcal{N}(vec(\bar{\Phi}), \Sigma_\nu \otimes \bar{\Omega}) \\ \Sigma_\nu^{posterior} &\sim \mathcal{IW}(\bar{\Sigma_\nu}, T + K + M + 2) \end{aligned}$$

In the spirit of the Minnesota prior, it is desirable to have a prior which assigns less impact to more distant lags. Hence, the BBE [2005] specification follows Kadiyala and Karlsson [1997]. First we draw Σ_ν from the posterior, where $\bar{\Sigma_\nu} =$

$\Sigma_{\nu,0} + \hat{V}'\hat{V} + \hat{\Phi}'[\Omega_0 + (F'_{T-1}F_{T-1})^{-1}]^{-1}\hat{\Phi}$ and where $\hat{V}$ is the matrix of OLS residuals. Then, conditional on the draw Σ_ν we draw from the posterior of the coefficients where $\bar{\Phi} = \bar{\Omega}(F'_{T-1}F_{T-1})\hat{\Phi}$ and $\bar{\Omega} = (\Omega_0^{-1} + (F'_{T-1}F_{T-1}))^{-1}$. To ensure stationarity, we truncate the draws and only accept values for Φ less than one in absolute values . This block on Kalman filter and smoother and the block on drawing the parameter space are iterated until convergence is achieved. For the implementation of the DCNW prior it required to set the diagonal elements of $\Sigma_{\nu,0}$ to the corresponding d-lag univariate autoregressions, σ_i^2. We construct the diagonal elements of Ω_0 such that the prior variances of the parameter of the k lagged j'th variable in the i'th equation equals $\sigma_i^2/k\sigma_j^2$.[12]

[12] For a detailed discussion of the implementation of the prior see the NBER working paper version of BBE (2004) and Kadiyala and Karlsson (1997).

B Data

All data are taken from the NBER's macroeconomic history database. Most of these data are contemporary and were collected for the business cycle dating project of Burns and Mitchell (1947). Our dataset includes a total of 164 time series.

Pos.	NBER Code	Description	TC	SA
1	1130	PIG IRON PRODUCTION	5	0
2	4051	INDEX OF THE GENERAL PRICE LEVEL	5	0
3	13012	FEDERAL RESERVE BANK DISCOUNT RATES, SAN FRANCISCO	1	0
4	14125	CURRENCY HELD BY THE PUBLIC	5	1
5	1054	INDEX OF PRODUCTION OF MANUFACTURES, SEASONALLY ADJUSTED	5	1
6	1055	INDEX OF PRODUCTION OF PRODUCERS GOODS	5	1
7	1056	INDEX OF PRODUCTION OF CONSUMERS GOOD	5	1
8	1057	INDEX OF PRODUCTION OF CONSUMERS GOODS, EXCLUDING AUTOMOBILES	5	1
9	01057A	INDEX OF PRODUCTION OF DURABLE GOODS	5	1
10	01057B	INDEX OF PRODUCTION OF TRANSIENT GOODS	5	1
11	1058	WHEAT FLOUR PRODUCTION	5	0
12	1060	CORN GRINDINGS	5	0
13	1064	TOTAL MEAT CONSUMPTION	5	0
14	1071	BUTTER CONSUMPTION	5	0
15	1105	PAPER PRODUCTION, ALL GRADES	5	0
16	01125A	CRUDE PETROLEUM CONSUMPTION, RUNS TO STILLS	5	0
17	1126	GASOLINE PRODUCTION AT REFINERIES	5	0
18	1131	MERCHANT PIG IRON PRODUCTION	5	1
19	1135	STEEL INGOT PRODUCTION	5	0
20	1144	AUTOMOBILE PRODUCTION, TRUCKS	5	0
21	1148	RAILROAD LOCOMOTIVE SHIPMENTS, DOMESTIC, BY CAR BUILDERS	5	0
22	1149	FREIGHT CAR SHIPMENTS, DOMESTIC	5	0
23	1171	WOODWORKING MACHINERY SHIPMENTS, VALUE	5	0
24	1175	INDEX OF PRODUCTION OF MANUFACTURES, TOTAL	5	0
25	01191B	INDEX OF COMMERCIAL PRODUCTION OF FOODSTUFFS AND TOBACCO	5	1
26	1204	INDEX OF PRODUCTION OF FUELS	5	1
27	1234	INDEX OF PRODUCTION OF DURABLE MANUFACTURES	5	1
28	1260	INDEX OF PRODUCTION OF MANUFACTURED FOOD PRODUCTS	5	1
29	3009	FREIGHT CAR SURPLUS	5	1
30	03016A	OPERATING REVENUES OF RAILROADS, PASSENGER	5	0
31	03016B	OPERATING REVENUES OF RAILROADS, FREIGHT	5	0
32	4001	WHOLESALE PRICE OF WHEAT, CHICAGO, SIX MARKETS	5	0
33	4005	WHOLESALE PRICE OF CORN, CHICAGO	5	0
34	4006	WHOLESALE PRICE OF COTTON, NEW YORK; 10 MARKETS	5	0
35	4007	WHOLESALE PRICE OF CATTLE, CHICAGO	5	0
36	4008	WHOLESALE PRICE OF HOGS, CHICAGO	5	0
37	4015	WHOLESALE PRICE OF COPPER, ELECTROLYTE, NEW YORK	5	0
38	4017	WHOLESALE PRICE OF PIG LEAD, NEW YORK	5	0
39	4030	WHOLESALE PRICE OF GRANULATED SUGAR	5	0
40	4034	WHOLESALE PRICE OF COFFEE	5	0
41	4048	INDEX OF WHOLESALE PRICES, BUREAU OF LABOR STATISTICS	5	0
42	4052	CONSUMER PRICE INDEX, ALL ITEMS LESS FOOD	5	0
43	4058	INDEX OF WHOLESALE PRICES OF FARM PRODUCTS	5	0
44	4061	INDEX OF WHOLESALE PRICES OF FOODS	5	0
45	4064	INDEX OF WHOLESALE PRICE OF TEXTILES	5	0
46	4066	WHOLESALE PRICES OF METAL AND METAL PRODUCTS	5	0
47	4068	INDEX OF WHOLESALE PRICES OF BUILDING MATERIALS	5	0
48	4071	INDEX OF RETAIL PRICES OF FOOD AT HOME	5	0
49	4074	WHOLESALE PRICE OF OATS, CHICAGO	5	0
50	4072	COST OF LIVING INDEX	5	0
51	4079	WHOLESALE PRICE OF CRUDE PETROLEUM, AT WELLS	5	0
52	4092	WHOLESALE PRICE OF SLAB ZINC	5	0
53	4099	WHOLESALE PRICE OF COMMON BRICKS, DOMESTIC, NEW YORK	5	0
54	4128	CONSUMER PRICE INDEX, ALL ITEMS	5	0
55	4129	WHOLESALE PRICE OF TEA	5	0

Pos.	NBER Code	Description	TC	SA
56	4134	WHOLESALE PRICE OF STRUCTURAL STEEL	5	0
57	4181	WHOLESALE PRICE OF STEEL RAILS	5	0
58	4189	INDEX OF WHOLESALE PRICES OF INDUSTRIAL COMMODITIES, BABSON	5	0
59	4202	INDEX OF WHOLESALE PRICES OF 15 SENSITIVE INDUSTRIAL RAW	5	0
60	06002A	INDEX OF DEPARTMENT STORE SALES	5	1
61	06002B	THE PHYSICAL VOLUME OF DEPARTMENT STORE SALES	5	1
62	6008	SALES BY GROCERY CHAIN STORES	5	0
63	6009	VARIETY CHAIN STORE SALES, ADJUSTED FOR TREND, PRICE	5	1
64	6029	INDEX OF ORDERS FOR MACHINE TOOLS AND FORGING MACHINERY	5	0
65	6058	INDEX OF TOTAL ADVERTISING	5	1
66	6059	INDEX OF WHOLESALE SALES OF SHOES	5	1
67	7001	DOMESTIC EXPORTS OF CRUDE FOODSTUFFS	5	0
68	7002	DOMESTIC EXPORTS OF MANUFACTURED FOODSTUFFS	5	0
69	7004	DOMESTIC EXPORTS OF SEMI-MANUFACTURES	5	0
70	7005	DOMESTIC EXPORTS OF FINISHED MANUFACTURES	5	0
71	7012	IMPORTS FOR CONSUMPTION OF CRUDE FOOD STUFFS	5	0
72	7013	IMPORTS OF MANUFACTURED FOODSTUFFS	5	0
73	7014	IMPORTS FOR CONSUMPTION OF CRUDE MATERIALS	5	0
74	7015	IMPORTS FOR CONSUMPTION OF SEMI-MANUFACTURES	5	0
75	7016	IMPORTS FOR CONSUMPTION OF FINISHED MANUFACTURES	5	0
76	7023	TOTAL EXPORTS	5	0
77	7028	TOTAL IMPORTS	5	0
78	8010B	PRODUCTION WORKER EMPLOYMENT, MANUFACTURING, TOTAL	5	0
79	8014	INDEX OF FACTORY EMPLOYMENT, PAPER AND PRINTING	5	1
80	8015	INDEX OF FACTORY EMPLOYMENT, IRON AND STEEL PRODUCTS	5	1
81	8016	INDEX OF FACTORY EMPLOYMENT, STONE, CLAY AND GLASS PRODUCTS	5	1
82	8017	INDEX OF FACTORY EMPLOYMENT, LUMBER AND PRODUCTS	5	1
83	8018	INDEX OF FACTORY EMPLOYMENT, MACHINERY	5	1
84	8046	AVERAGE WEEKLY EARNINGS, REPRESENTATIVE FACTORIES	5	0
85	8061	INDEX OF COMPOSITE WAGES	5	0
86	8069	INDEX OF AGGREGATE WEEKLY PAYROLLS, PRODUCTION WORKERS TOTAL MANUFACTURING	5	0
87	8071	INDEX OF FACTORY PAYROLLS, TEXTILES	5	0
88	8072	INDEX OF FACTORY PAYROLLS, PAPER AND PRINTING	5	0
89	8073	INDEX OF FACTORY PAYROLLS, IRON AND STEEL PRODUCTS	5	0
90	8074	INDEX OF FACTORY PAYROLLS, STONE CLAY AND GLASS	5	0
91	8075	INDEX OF FACTORY PAYROLLS - LUMBER AND PRODUCTS	5	0
92	8076	INDEX OF FACTORY PAYROLLS, MACHINERY	5	0
93	8078	INDEX OF FACTORY PAYROLLS, NEW YORK STATE FACTORIES	5	0
94	8088	INDEX OF FACTORY EMPLOYMENT-BAKING	5	0
95	8101	INDEX OF FACTORY EMPLOYMENT, LEATHER AND MANUFACTURES	5	1
96	8104	INDEX OF FACTORY EMPLOYMENT, PAPER AND PULP	5	1
97	8106	INDEX OF EMPLOYMENT, HARDWARE	5	1
98	8110	INDEX OF FACTORY PAYROLLS, CANE SUGAR REFINING	5	0
99	8112	INDEX OF FACTORY PAYROLLS, BAKING	5	0
100	8114	INDEX OF FACTORY PAYROLLS, TOBACCO MANUFACTURES	5	0
101	8145	INDEX OF FACTORY PAYROLLS, AUTOMOBILES	5	0
102	8261	AVERAGE WEEKLY EARNINGS, MANUFACTURING, TOTAL	5	0
103	11001	BOND SALES, PAR VALUE	5	0
104	11005	AMERICAN RAILROAD STOCK PRICES	5	0
105	11009	INDUSTRIAL STOCK PRICE INDEX, DOW-JONES	5	0
106	11025	INDEX OF ALL COMMON STOCK PRICES, COWLES COMMISSION AND S& P CORPORATION	5	0
107	12002A	INDEX OF INDUSTRIAL ACTIVITY	5	0
108	12003	INDEX OF AMERICAN BUSINESS ACTIVITY	5	0
109	12004	INDEX OF INDUSTRIAL PRODUCTION AND TRADE	5	1
110	12007	INDEX OF AMERICAN BUSINESS ACTIVITY	5	0
111	12009A	INDEX OF BUSINESS ACTIVITY, PITTSBURGH	5	1
112	12009	INDEX OF AGRICULTURAL MARKETINGS	5	1
113	12013	BANK CLEARINGS, DAILY AVERAGE	5	0
114	13001	CALL MONEY RATES, MIXED COLLATERAL	1	0
115	13002	COMMERCIAL PAPER RATES, NEW YORK CITY	5	0
116	13003	NINETY DAY TIME-MONEY RATES ON STOCK EXCHANGE LOANS	1	0

Pos.	NBER Code	Description	TC	SA
117	13004	RATES ON CUSTOMER LOANS, NEW YORK CITY	1	0
118	13005	RATES ON CUSTOMERS LOANS, NORTHERN AND WESTERN CITIES	1	0
119	13006	BANK RATES ON CUSTOMERS LOANS, SOUTHERN AND WESTERN CITIES	1	0
120	13007	BANKER S ACCEPTANCE RATES, NEW YORK CITY	1	0
121	13008	INTEREST RATES ON FEDERAL LAND BANK LOANS, TWELVE FEDERAL LAND BANKS	1	0
122	13009	DISCOUNT RATES, FEDERAL RESERVE BANK OF NEW YORK	1	0
123	13010	FEDERAL RESERVE BANK DISCOUNT RATES, MINNEAPOLIS	1	0
124	13011	FEDERAL RESERVE BANK DISCOUNT RATE, DALLAS	1	0
125	13021	INDEX OF YIELDS OF HIGH GRADE CORPORATE AND MUNICIPAL BONDS	1	0
126	13023	INDEX OF YIELDS OF HIGH GRADE MUNICIPAL BONDS	1	0
127	13024	YIELDS OF HIGH GRADE RAILROAD BONDS	1	0
128	13025	INDEX OF YIELDS OF HIGH GRADE PUBLIC UTILITY BONDS	1	0
129	13026	YIELD ON HIGH GRADE INDUSTRIAL BONDS, AAA RATING	1	0
130	13030	WEIGHTED AVERAGE OF OPEN MARKET RATES, NEW YORK CITY	1	0
131	13031	BANK RATES ON CUSTOMER LOANS, LEADING CITIES	1	0
132	13032	TOTAL RATES CHARGED CUSTOMERS AND OPEN MARKET RATES, COMBINED	1	0
133	13033	YIELD ON LONG-TERM UNITED STATES BONDS	1	0
134	13035	YIELDS ON CORPORATE BONDS, HIGHEST RATING	1	0
135	13036	YIELDS ON CORPORATE BONDS, LOWEST RATING	1	0
136	13048	DIVIDEND YIELD OF PREFERRED STOCK ON THE NEW YORK STOCK EXCHANGE	1	0
137	14062	TOTAL GOLD RESERVES OF FEDERAL RESERVE BANKS	5	0
138	14063	CASH RESERVES OF FEDERAL RESERVE BANKS	5	0
139	14064	RESERVES HELD AT FEDERAL RESERVE BANKS, ALL MEMBER BANKS	5	0
140	14065	NOTES IN CIRCULATION, FEDERAL RESERVE BANKS	5	0
141	14066	TOTAL BILLS AND SECURITIES HELD BY FEDERAL RESERVE BANKS	5	0
142	14067	BILLS DISCOUNTED, FEDERAL RESERVE BANKS	5	0
143	14069	GOVERNMENT SECURITIES HELD, FEDERAL RESERVE BANKS	5	0
144	14070	TOTAL DEPOSITS, FEDERAL RESERVE BANKS	5	0
145	14072	RATIO OF RESERVES TO NOTE AND DEPOSIT LIABILITIES, FEDERAL RESERVE BANKS	5	0
146	14076	MONETARY GOLD STOCK	5	0
147	14078	NET DEMAND DEPOSITS, REPORTING MEMBER BANKS, FEDERAL RESERVE SYSTEM	5	0
148	14079	TIME DEPOSITS, REPORTING MEMBER BANKS, FEDERAL RESERVE SYSTEM	5	0
149	14080	CURRENCY HELD BY THE TREASURY	5	1
150	14086	PERCENTAGE OF RESERVES HELD TO RESERVES REQUIRED, ALL MEMBER BANKS, FRB SYSTEM	5	0
151	14121	NEW YORK CITY	5	0
152	14126	VAULT CASH, ALL BANKS EXCEPT FEDERAL RESERVE BANKS	5	0
153	14127	INVESTMENTS OTHER THAN UNITED STATES GOVERNMENT SECURITIES, REPORTING FEDERAL RESERVE MEMBER BANKS IN 101 LEADING CITIES	5	0
154	14135	TOTAL CURRENCY OUTSIDE THE TREASURY AND FEDERAL RESERVE BANKS, END OF MONTH	5	0
155	14137	GOLD HELD IN THE TREASURY AND FEDERAL RESERVE BANKS, END OF	5	0
156	14144	MONEY STOCK, COMMERICAL BANKS PLUS CURRENCY HELD BY PUBLIC	5	0
157	14145	TOTAL DEPOSITS, ALL COMMERCIAL BANKS	5	1
158	14172	ADJUSTED DEMAND DEPOSITS, ALL COMMERCIAL BANKS	5	1
159	14173	DEPOSITS IN MUTUAL SAVINGS BANKS AND POSTAL SAVINGS SYSTEM, END OF MONTH	5	0
160	14174	ADJ. DEMAND DEPOSITS, ALL COMMERCIAL BANKS,CURRENCY HELD BY PUBLIC	5	1
161	14175	ADJ. DEMAND DEPOSITS, ALL BANKS,TOTAL TIME DEPOSITS, CURRENCY HELD BY PUBLIC	5	1
162	14178	RATIO OF CURRENCY HELD BY THE PUBLIC TO ADJUSTED DEMAND DEPOSITS, TIME DEPOSITS, ALL COMMERCIAL BANKS, PLUS CURRENCY HELD BY THE PUBLIC	5	1
163	14190	PERCENT CHANGE IN TOTAL MONEY SUPPLY, MONTH-TO-MONTH CHANGE	1	1
164	14195	MONEY STOCK, MONTH-TO-MONTH CHANGE	1	

SA = 0: no seasonal adjustment or SA in the source; SA = 1: seasonally adjusted by the authors. TC = 1: no transformation; TC = 5: 1st difference of logs.

C Tables

Table 3: **Estimated R^2s from regressions of individual series on FAVAR (DR model).**

Description	R^2	**Description**	R^2
PR IMNF	1	Production (durable mnfct)	0.71
CPI	1	Industrial Production/Trade	0.69
DR	1	Industrial activity	0.68
Total rates charged	1	Business activity growth	0.67
Bankers rates (Customer loans)	1	Index of WSP:	0.61
Open market rates	0.99	WSP: Foods	0.6
CommPR	0.99	General price level	0.56
Yield:Corporate bonds	0.99	Employment: Machinery	0.54
Yields: Corporate bonds	0.99	CPI less food	0.53
Rates on custom. Loans	0.99	PR IPTG	0.53
Rates on custom. Loans (SW)	0.99	Pig Iron	0.51
90day time to money	0.99	Employment: Manufacturing	0.51
Rates on custom. Loans (NW)	0.99	Business activity pittsburgh	0.5
Yields: Public utility	0.98	Index manufacturing prod.	0.5
Banker s accept. Rate	0.98	Steel ingot	0.5
DR Dallas	0.98	Cost of Living index	0.49
DR SF	0.97	Payrolls wkly: Manufacturing	0.49
DR Minneapolis	0.96	Factory payrolls: Machinery	0.49
Yields: Industrial bonds	0.96	Factory payrolls: steel	0.47
Call money rate	0.95	Employment: Steel	0.47
Yield: Long-term bonds	0.95	PR IPDCG	0.45
Yields: Railroad bonds	0.95	WSP Industrial (sensitive Raw)	0.44
Dividend yields	0.95	WSP: Textiles	0.44
Yields: Munic Interest rates FED bank loans	0.91	PR IPCGLA	0.4
PR IPRGD	0.88	Employment: Paper	0.39
WSP: food	0.87	WSP Industrial commodities	0.39
PR IPDG	0.81	Employment: Lumber	0.37
Yield:Corporate bonds (LG)	0.78	WSP: Building material	0.37
Index business activity	0.77	Employment: Steel	0.37

Data show the variance decomposition of the factors through the estimated R^2s for each indicator series based on 4 extracted factors.

Table 4: **Forecast error variance decomposition of a contractionary monetary policy shock**

			Commercial Paper Rate Model					
Horizon	0	1	2	3	6	12	24	48
CommPR	5	6	7	7	6	6	5	5
FRB Industrial Production	5	6	8	8	8	9	9	10
CPI inflation	65	48	46	44	43	43	43	42
S&P 500	9	11	13	14	15	15	16	16
Wages	12	14	15	15	15	15	16	16
Orders of Machinery Tools	9	13	14	18	18	20	20	20
			Discount Rate Model					
Horizon	0	1	2	3	6	12	24	48
Discount Rate	4	5	5	5	5	6	6	6
FRB Industrial Production	4	4	5	6	6	7	7	9
CPI inflation	94	56	53	52	48	46	45	43
S&P 500	5	6	6	7	8	9	9	10
Wages	10	11	11	11	11	12	12	13
Orders of Machinery Tools	6	7	7	9	10	10	11	11
			M0 Model					
Horizon	0	1	2	3	6	12	24	48
M0	4	4	4	4	3	3	3	3
FRB Industrial Production	15	18	19	18	18	20	21	20
CPI inflation	54	38	38	37	37	37	36	35
S&P 500	16	18	20	22	22	22	22	21
Wages	10	10	12	12	12	13	12	12
Orders of Machinery Tools	18	17	20	23	23	23	23	22
			M1 Model					
Horizon	0	1	2	3	6	12	24	48
M1	17	19	19	18	17	18	17	16
FRB Industrial Production	16	17	17	17	17	17	16	16
CPI inflation	89	60	55	54	50	48	47	42
S&P 500	19	20	21	22	22	22	23	23
Wages	16	17	18	18	17	17	16	16
Orders of Machinery Tools	22	23	26	27	26	26	26	27
			M2 Model					
Horizon	0	1	2	3	6	12	24	48
M2	3	3	2	2	2	2	3	3
FRB Industrial Production	4	4	5	6	6	6	7	7
CPI inflation	87	48	45	40	38	37	37	36
S&P 500	5	6	6	8	8	9	9	10
Wages	10	9	11	10	11	10	11	11
Orders of Machinery Tools	7	7	8	9	10	11	11	12

Percentage forecast error variance decompositions of a contractionary monetary policy shock for the 3 models considered. The respective 3 blocks report the results for the discount rate model, commercial paper rates model, M0 model the M1 model and the M2 model. The variables considered are the same as for the impulse response analysis, namely the Discount Rate, the commercial Paper rate, the growth in FRB index for production in manufacturing, the CPI inflation, S&P is the Standard and Poor 500 index and the index of orders in Machinery and Tools. The values denote the variance explained in the respective series due to a monetary policy shock in percent based on the median of the posterior draws.

Table 5: **RMSFE at horizon 1 for different models considered.**

Horizon: 1	FRB Ind. Prod.	CPI Inflation	Orders	Policy variable
Commercial Paper Rate Model				
Before Great Crash	5.85,[12.01,2.36]	1.27,[2.66,0.69]	26.35,[41.49,15.50]	133.09,[145.70,129.35]
Before 1^{st} Banking Crisis	8.40,[16.42,2.85]	2.04,[3.80,0.90]	27.24,[38.82,17.58]	133.78,[148.89,129.46]
Before German Banking Crisis	4.59,[9.26,2.03]	1.07,[2.01,0.65]	20.62,[33.04,13.66]	130.47,[135.20,129.12]
Before Devaluation of $	3.23,[6.73,1.78]	0.91,[1.53,0.63]	20.05,[31.91,13.58]	130.23,[134.53,129.13]
Before "Banking Holiday"	2.67,[4.77,1.74]	0.75,[1.15,0.61]	16.33,[21.89,12.88]	131.01,[137.08,129.20]
Discount Rate Model				
Before Great Crash	7.03,[9.79,4.83]	1.11,[1.58,0.93]	26.21,[32.67,21.52]	216.26,[218.28,215.25]
Before 1^{st} Banking Crisis	4.81,[8.17,3.64]	1.01,[1.47,0.91]	22.33,[26.70,20.50]	222.20,[227.63,218.69]
Before German Banking Crisis	5.31,[7.12,4.05]	0.96,[1.14,0.91]	22.57,[26.96,20.92]	227.06,[231.73,223.60]
Before Devaluation of $	6.05,[8.43,4.32]	0.98,[1.25,0.91]	24.44,[30.78,21.89]	229.63,[235.72,224.73]
Before "Banking Holiday"	5.32,[6.70,4.22]	0.96,[1.10,0.91]	22.04,[24.33,20.52]	225.14,[229.18,221.86]
M0 Model				
Before Great Crash	2.88,[3.50,2.69]	1.03,[1.16,0.99]	22.32,[23.73,21.51]	2.36,[2.45,2.34]
Before 1^{st} Banking Crisis	2.82,[3.35,2.69]	1.02,[1.11,0.99]	22.89,[24.05,22.09]	2.36,[2.45,2.34]
Before German Banking Crisis	2.83,[3.22,2.68]	1.02,[1.11,0.99]	24.32,[26.97,22.28]	2.52,[2.69,2.40]
Before Devaluation of $	2.88,[3.42,2.69]	1.03,[1.14,0.99]	24.95,[27.34,23.23]	2.47,[2.65,2.37]
Before "Banking Holiday"	3.20,[4.04,2.74]	1.02,[1.14,0.99]	22.99,[25.03,21.98]	2.49,[2.85,2.35]
M1 Model				
Before Great Crash	2.48,[2.87,2.38]	0.81,[0.96,0.76]	24.33,[25.32,23.76]	3.73,[3.76,3.72]
Before 1^{st} Banking Crisis	2.55,[3.08,2.39]	0.83,[1.03,0.77]	25.26,[26.32,24.38]	3.76,[3.88,3.72]
Before German Banking Crisis	2.55,[3.15,2.39]	0.82,[0.99,0.77]	25.91,[27.98,24.72]	3.75,[3.87,3.72]
Before Devaluation of $	2.49,[2.83,2.38]	0.82,[0.95,0.77]	24.46,[26.35,23.21]	3.75,[3.83,3.72]
Before "Banking Holiday"	2.51,[3.00,2.38]	0.92,[1.12,0.78]	23.68,[25.29,22.94]	3.75,[3.84,3.72]
M2 Model				
Before Great Crash	5.16,[5.52,5.04]	0.44,[0.63,0.38]	22.77,[24.04,22.02]	2.10,[2.25,2.05]
Before 1^{st} Banking Crisis	5.11,[5.42,5.04]	0.45,[0.64,0.38]	24.12,[25.63,22.84]	2.08,[2.18,2.05]
Before German Banking Crisis	5.13,[5.44,5.04]	0.47,[0.72,0.38]	23.70,[25.13,22.81]	2.08,[2.21,2.05]
Before Devaluation of $	5.16,[5.54,5.05]	0.54,[0.87,0.40]	27.35,[30.14,25.17]	18.00,[19.17,17.31]
Before "Banking Holiday"	5.23,[5.87,5.05]	0.48,[0.71,0.39]	24.74,[27.02,22.98]	2.09,[2.23,2.05]
No Policy Instrument Model				
Before Great Crash	5.72,[6.18,5.63]	3.02,[3.71,2.70]	2.94,[4.96,2.17]	
Before 1^{st} Banking Crisis	4.96,[5.84,4.52]	7.50,[7.89,7.40]	3.73,[5.02,2.91]	
Before German Banking Crisis	4.97,[5.28,4.89]	7.45,[7.90,7.25]	2.90,[4.06,2.37]	
Before Devaluation of $	4.11,[4.67,3.95]	10.90,[12.15,9.67]	3.23,[4.69,2.53]	
Before "Banking Holiday"	5.04,[5.39,4.94]	5.58,[6.23,5.23]	2.77,[4.11,2.05]	

The table reports the median root mean squared forecast errors (RMSFE) and its 68% highest posterior density in brackets for the respective models under consideration.

Table 6: **RMSFE at horizon 3 for different models considered.**

Horizon: 3	FRB Ind. Prod.	CPI Inflation	Orders	Policy variable
Commercial Paper Rate Model				
Before Great Crash	10.25,[18.37,5.08]	2.27,[4.19,1.25]	26.62,[41.01,16.22]	175.41,[277.21,127.55]
Before 1^{st} Banking Crisis	13.40,[22.12,6.76]	2.86,[4.69,1.57]	29.32,[41.70,18.86]	173.18,[280.22,128.50]
Before German Banking Crisis	7.02,[13.53,3.43]	1.60,[2.87,0.92]	21.16,[33.21,13.88]	137.95,[187.04,122.88]
Before Devaluation of $	5.33,[10.14,2.84]	1.37,[2.31,0.82]	19.91,[31.60,13.43]	131.54,[172.45,122.19]
Before "Banking Holiday"	4.58,[7.70,2.60]	1.28,[1.92,0.85]	17.64,[23.50,13.65]	162.30,[230.61,127.54]
Discount Rate Model				
Before Great Crash	8.09,[11.60,5.43]	1.46,[2.26,1.04]	25.03,[31.20,20.66]	207.81,[218.92,204.04]
Before 1^{st} Banking Crisis	5.54,[9.91,4.06]	1.20,[1.99,0.95]	21.51,[26.03,19.64]	217.85,[239.00,207.57]
Before German Banking Crisis	5.43,[7.39,4.26]	1.04,[1.36,0.91]	21.83,[26.03,20.05]	236.14,[254.55,222.72]
Before Devaluation of $	6.26,[9.06,4.73]	1.14,[1.62,0.93]	23.67,[29.80,21.08]	244.87,[269.52,225.58]
Before "Banking Holiday"	5.35,[6.95,4.33]	1.02,[1.28,0.90]	21.27,[23.85,19.61]	231.85,[249.14,218.80]
M0 Model				
Before Great Crash	3.17,[4.05,2.72]	1.07,[1.26,0.97]	22.91,[23.97,22.14]	2.26,[2.38,2.21]
Before 1^{st} Banking Crisis	3.11,[4.16,2.67]	1.04,[1.24,0.96]	22.23,[23.25,21.58]	2.26,[2.39,2.20]
Before German Banking Crisis	3.00,[3.53,2.70]	1.02,[1.17,0.95]	23.28,[25.59,21.71]	2.40,[2.59,2.28]
Before Devaluation of $	3.15,[3.80,2.78]	1.05,[1.23,0.96]	23.88,[25.90,22.55]	2.41,[2.61,2.28]
Before "Banking Holiday"	3.55,[4.67,2.86]	1.08,[1.29,0.97]	22.47,[24.09,21.60]	2.63,[3.12,2.33]
M1 Model				
Before Great Crash	3.34,[4.45,2.61]	0.92,[1.15,0.79]	26.02,[27.90,24.85]	3.50,[3.56,3.47]
Before 1^{st} Banking Crisis	3.61,[4.94,2.80]	0.96,[1.18,0.81]	28.84,[30.39,27.50]	3.61,[3.79,3.51]
Before German Banking Crisis	3.27,[4.41,2.58]	0.90,[1.13,0.77]	29.59,[31.86,27.61]	3.62,[3.82,3.52]
Before Devaluation of $	3.09,[3.77,2.59]	0.85,[0.99,0.76]	28.01,[30.11,26.34]	3.55,[3.66,3.49]
Before "Banking Holiday"	3.43,[4.76,2.67]	0.94,[1.16,0.80]	26.87,[29.12,25.49]	3.56,[3.67,3.50]
M2 Model				
Before Great Crash	5.24,[6.04,4.84]	0.66,[0.98,0.47]	22.60,[23.67,21.94]	2.09,[2.34,1.97]
Before 1^{st} Banking Crisis	5.10,[5.90,4.80]	0.67,[0.99,0.47]	23.36,[24.65,22.38]	2.02,[2.17,1.95]
Before German Banking Crisis	5.35,[6.24,4.90]	0.68,[0.97,0.47]	23.06,[24.29,22.30]	2.06,[2.24,1.96]
Before Devaluation of $	5.20,[6.01,4.83]	0.88,[1.39,0.55]	26.19,[28.72,24.36]	18.51,[21.92,16.51]
Before "Banking Holiday"	5.46,[6.75,4.89]	0.67,[1.01,0.47]	23.87,[25.80,22.53]	2.04,[2.24,1.95]
No Policy Instrument Model				
Before Great Crash	5.67,[6.27,5.37]	3.19,[4.03,2.76]	3.04,[4.98,2.21]	
Before 1^{st} Banking Crisis	5.13,[6.16,4.53]	7.24,[7.81,7.00]	3.65,[4.88,2.80]	
Before German Banking Crisis	5.52,[6.49,4.90]	11.41,[12.48,10.40]	3.12,[4.24,2.58]	
Before Devaluation of $	4.33,[5.07,3.91]	10.32,[11.48,9.19]	3.57,[4.94,2.87]	
Before "Banking Holiday"	5.11,[5.61,4.84]	6.33,[7.20,5.67]	2.95,[4.18,2.21]	

The table reports the median root mean squared forecast errors (RMSFE) and its 68% highest posterior density in brackets for the respective models under consideration.

Table 7: **RMSFE at horizon 6 for different models considered.**

Horizon: 6	FRB Ind. Prod.	CPI Inflation	Orders	Policy variable
Commercial Paper Rate Model				
Before Great Crash	12.30,[20.24,7.05]	3.43,[5.87,1.94]	28.70,[44.83,17.80]	289.42,[542.88,150.07]
Before 1^{st} Banking Crisis	14.84,[22.48,8.92]	3.31,[4.96,2.12]	29.57,[42.01,19.50]	285.84,[545.34,152.04]
Before German Banking Crisis	8.15,[13.96,4.58]	2.03,[3.40,1.21]	21.27,[32.70,13.99]	191.07,[350.66,124.44]
Before Devaluation of $	6.72,[11.28,3.80]	1.68,[2.83,1.02]	20.31,[31.42,13.67]	166.75,[301.88,119.88]
Before "Banking Holiday"	5.64,[8.82,3.55]	2.22,[3.24,1.43]	19.54,[27.56,14.41]	257.96,[412.17,147.00]
Discount Rate Model				
Before Great Crash	8.43,[11.62,6.04]	1.79,[2.79,1.19]	24.53,[30.89,20.29]	227.52,[280.63,196.91]
Before 1^{st} Banking Crisis	6.24,[11.07,4.50]	1.35,[2.45,0.99]	21.78,[26.41,19.68]	209.59,[262.18,194.64]
Before German Banking Crisis	6.35,[8.21,5.04]	1.14,[1.52,0.95]	22.82,[26.73,20.43]	229.69,[262.91,209.85]
Before Devaluation of $	7.41,[10.01,5.72]	1.30,[1.93,1.00]	24.83,[30.57,21.74]	242.30,[287.81,213.92]
Before "Banking Holiday"	6.06,[7.54,4.97]	1.11,[1.41,0.93]	22.20,[25.34,20.06]	229.05,[257.82,207.66]
M0 Model				
Before Great Crash	3.90,[4.99,3.16]	1.15,[1.46,0.99]	24.44,[25.63,23.73]	2.26,[2.44,2.14]
Before 1^{st} Banking Crisis	3.97,[5.39,3.08]	1.19,[1.52,1.00]	25.43,[26.70,24.37]	2.22,[2.42,2.11]
Before German Banking Crisis	3.32,[4.03,2.86]	1.08,[1.31,0.95]	26.37,[28.55,24.71]	2.26,[2.45,2.14]
Before Devaluation of $	3.77,[4.65,3.09]	1.15,[1.38,0.98]	27.20,[29.19,25.62]	2.26,[2.46,2.13]
Before "Banking Holiday"	4.42,[5.60,3.53]	1.21,[1.45,1.03]	25.37,[27.19,24.24]	2.61,[3.10,2.27]
M1 Model				
Before Great Crash	3.59,[4.69,2.81]	1.10,[1.44,0.87]	25.38,[26.62,24.56]	3.25,[3.33,3.20]
Before 1^{st} Banking Crisis	4.08,[5.47,3.14]	1.29,[1.64,1.03]	26.85,[28.30,25.66]	3.49,[3.73,3.34]
Before German Banking Crisis	3.53,[4.61,2.83]	1.04,[1.30,0.86]	27.55,[29.62,25.82]	3.40,[3.61,3.28]
Before Devaluation of $	3.34,[4.11,2.74]	0.95,[1.15,0.81]	26.13,[28.00,24.69]	3.33,[3.46,3.25]
Before "Banking Holiday"	3.77,[5.04,2.93]	1.06,[1.31,0.86]	25.23,[27.11,24.26]	3.35,[3.49,3.26]
M2 Model				
Before Great Crash	5.26,[6.26,4.73]	0.80,[1.21,0.57]	22.44,[23.67,21.83]	2.13,[2.51,1.93]
Before 1^{st} Banking Crisis	5.14,[6.07,4.63]	0.83,[1.13,0.62]	23.83,[25.42,22.53]	1.96,[2.17,1.85]
Before German Banking Crisis	5.58,[6.69,4.91]	0.88,[1.22,0.64]	23.89,[25.54,22.63]	2.00,[2.22,1.87]
Before Devaluation of $	5.15,[6.00,4.69]	1.02,[1.48,0.70]	26.00,[28.39,24.09]	19.76,[25.34,16.08]
Before "Banking Holiday"	5.54,[6.72,4.79]	0.82,[1.17,0.58]	23.92,[26.03,22.55]	1.98,[2.21,1.85]
No Policy Instrument Model				
Before Great Crash	5.54,[6.26,5.12]	3.81,[4.97,3.15]	3.17,[5.11,2.30]	
Before 1^{st} Banking Crisis	5.36,[6.55,4.58]	7.01,[7.86,6.63]	3.62,[4.83,2.80]	
Before German Banking Crisis	5.34,[6.28,4.72]	10.59,[11.64,9.65]	3.47,[4.65,2.83]	
Before Devaluation of $	4.37,[5.12,3.85]	9.62,[10.70,8.58]	3.43,[4.78,2.75]	
Before "Banking Holiday"	5.24,[5.88,4.79]	7.15,[8.03,6.38]	3.33,[4.44,2.68]	

The table reports the median root mean squared forecast errors (RMSFE) and its 68% highest posterior density in brackets for the respective models under consideration.

Table 8: **RMSFE at horizon 12 for different models considered.**

Horizon: 12	FRB Ind. Prod.	CPI Inflation	Orders	Policy variable
Commercial Paper Rate Model				
Before Great Crash	13.56,[20.31,9.14]	4.07,[6.61,2.51]	33.09,[52.76,20.59]	457.83,[903.31,217.92]
Before 1^{st} Banking Crisis	15.49,[22.26,10.58]	3.52,[5.04,2.46]	31.20,[45.39,21.72]	463.94,[891.51,217.75]
Before German Banking Crisis	8.94,[13.76,5.68]	2.38,[3.73,1.53]	22.91,[34.13,15.93]	322.01,[632.84,155.79]
Before Devaluation of $	7.35,[11.43,4.60]	2.03,[3.15,1.31]	21.52,[31.66,14.99]	268.69,[558.88,141.01]
Before "Banking Holiday"	6.95,[10.22,4.66]	2.58,[3.64,1.70]	25.61,[37.56,17.56]	337.30,[582.45,171.61]
Discount Rate Model				
Before Great Crash	8.55,[11.55,6.37]	1.99,[2.91,1.40]	26.35,[32.83,22.68]	269.33,[390.45,196.51]
Before 1^{st} Banking Crisis	7.14,[11.58,5.54]	1.53,[2.80,1.10]	25.29,[30.96,22.75]	212.80,[370.87,181.15]
Before German Banking Crisis	6.79,[8.29,5.68]	1.41,[1.85,1.12]	26.29,[30.48,23.67]	218.65,[263.32,196.30]
Before Devaluation of $	7.49,[9.74,6.07]	1.60,[2.31,1.21]	27.59,[33.20,24.49]	240.79,[323.19,206.28]
Before "Banking Holiday"	7.00,[8.29,5.98]	1.40,[1.73,1.15]	26.75,[30.33,24.05]	212.68,[245.60,191.29]
M0 Model				
Before Great Crash	3.96,[5.04,3.24]	1.26,[1.64,1.03]	23.71,[24.88,22.95]	2.10,[2.30,1.96]
Before 1^{st} Banking Crisis	4.43,[5.75,3.60]	1.59,[2.08,1.24]	24.33,[25.84,23.32]	2.09,[2.30,1.95]
Before German Banking Crisis	3.37,[4.05,2.87]	1.23,[1.54,1.00]	24.66,[26.54,23.29]	2.15,[2.39,1.99]
Before Devaluation of $	3.88,[4.84,3.21]	1.37,[1.65,1.14]	25.42,[27.24,24.02]	2.20,[2.46,2.02]
Before "Banking Holiday"	4.66,[5.78,3.77]	1.36,[1.66,1.12]	24.35,[26.11,23.19]	2.68,[3.17,2.31]
M1 Model				
Before Great Crash	3.65,[4.69,2.92]	1.16,[1.50,0.92]	24.43,[25.91,23.61]	2.93,[3.06,2.85]
Before 1^{st} Banking Crisis	4.39,[5.66,3.54]	1.47,[1.84,1.20]	25.84,[27.49,24.66]	3.40,[3.71,3.19]
Before German Banking Crisis	3.70,[4.71,3.00]	1.16,[1.45,0.94]	26.13,[28.22,24.56]	3.18,[3.42,3.02]
Before Devaluation of $	3.54,[4.31,2.95]	1.05,[1.25,0.87]	25.09,[26.78,23.68]	3.08,[3.24,2.96]
Before "Banking Holiday"	4.15,[5.33,3.29]	1.15,[1.44,0.92]	24.27,[26.30,23.14]	3.14,[3.35,2.98]
M2 Model				
Before Great Crash	5.11,[6.07,4.50]	1.14,[1.62,0.85]	25.14,[26.68,24.26]	2.48,[2.85,2.19]
Before 1^{st} Banking Crisis	5.23,[6.14,4.59]	1.31,[1.62,1.05]	27.74,[29.80,26.31]	2.11,[2.34,1.95]
Before German Banking Crisis	5.66,[6.82,4.95]	1.33,[1.68,1.06]	28.16,[30.33,26.48]	2.11,[2.36,1.93]
Before Devaluation of $	5.15,[6.16,4.53]	1.28,[1.78,0.95]	28.12,[30.57,26.42]	22.03,[29.84,16.09]
Before "Banking Holiday"	5.39,[6.59,4.64]	1.10,[1.45,0.84]	26.76,[28.85,25.30]	2.09,[2.34,1.92]
No Policy Instrument Model				
Before Great Crash	5.44,[6.24,4.91]	3.92,[5.16,3.22]	3.44,[5.41,2.56]	
Before 1^{st} Banking Crisis	5.84,[7.14,4.92]	9.12,[10.24,8.31]	4.02,[5.44,3.19]	
Before German Banking Crisis	5.01,[5.83,4.41]	9.36,[10.25,8.54]	3.35,[4.72,2.64]	
Before Devaluation of $	4.52,[5.29,3.91]	8.57,[9.56,7.67]	3.53,[4.86,2.79]	
Before "Banking Holiday"	5.06,[5.68,4.60]	6.55,[7.36,5.85]	3.54,[4.58,2.85]	

The table reports the median root mean squared forecast errors (RMSFE) and its 68% highest posterior density in brackets for the respective models under consideration.

D Figures, Whole Observation Period 1919-1939

D.1 Reduced Form Results

Figure 1: **Extracted Factors with 95% probability bands**

In order to access the uncertainty associated with the sampled posterior factors we report the 95 % probability bands around the posterior median of the respective sampled factors. These are fairly tight indicating a low degree of sampling uncertainty. We furthermore checked the convergence by monitoring the sampler visually through trace plots. Figure (3)) shows how the parameter estimates evolve in the sampling process and helps to check whether there are jumps in the level of the respective parameter. Furthermore we plotted the first half of the kept draws against the second half to check whether the sampler has converged and whether the whole density of the distribution is represented. Figure (2) shows hardly any deviation, suggesting that the sampler converged already in the first half.

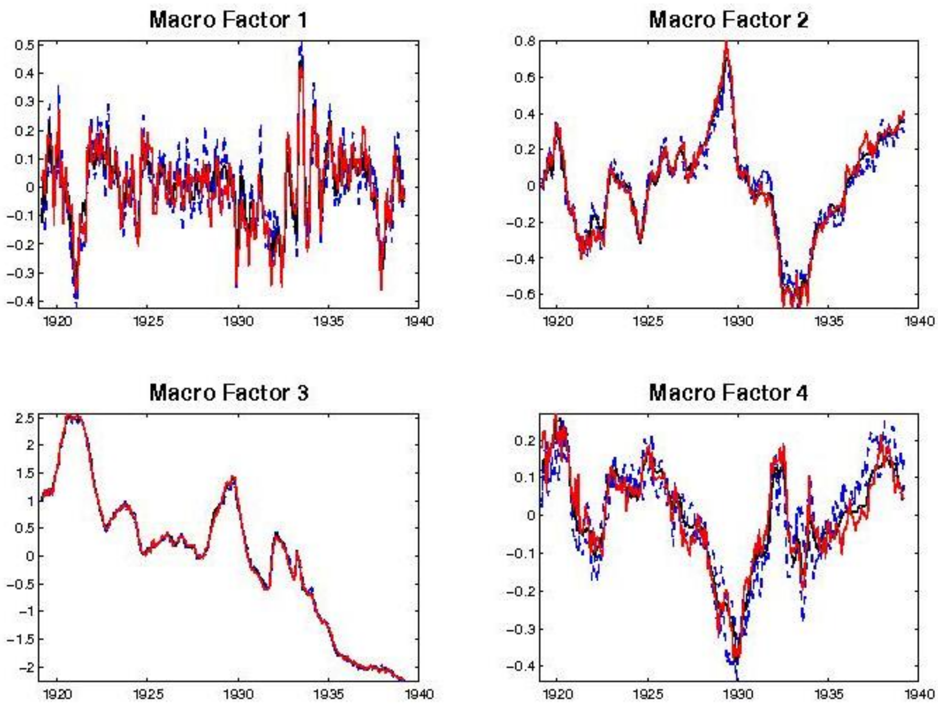


Figure 2: **Graphical convergence plot for extracted factors**

In order to monitor the graphical convergence of the sampler we plot the first half of the kept draws against the second half of the draws of the sampled posterior factors and check the degree of deviation. This is another strategy among many others in order to check the convergence properties of the sampler. If a very small degree or even no deviation is visible one can gain confidence that the sampler went through the whole distribution and has converged to the target distribution and did not stuck in a local mode. From the results depicted on the four panels one can see that problems with the convergence of the sampler is not an issue.

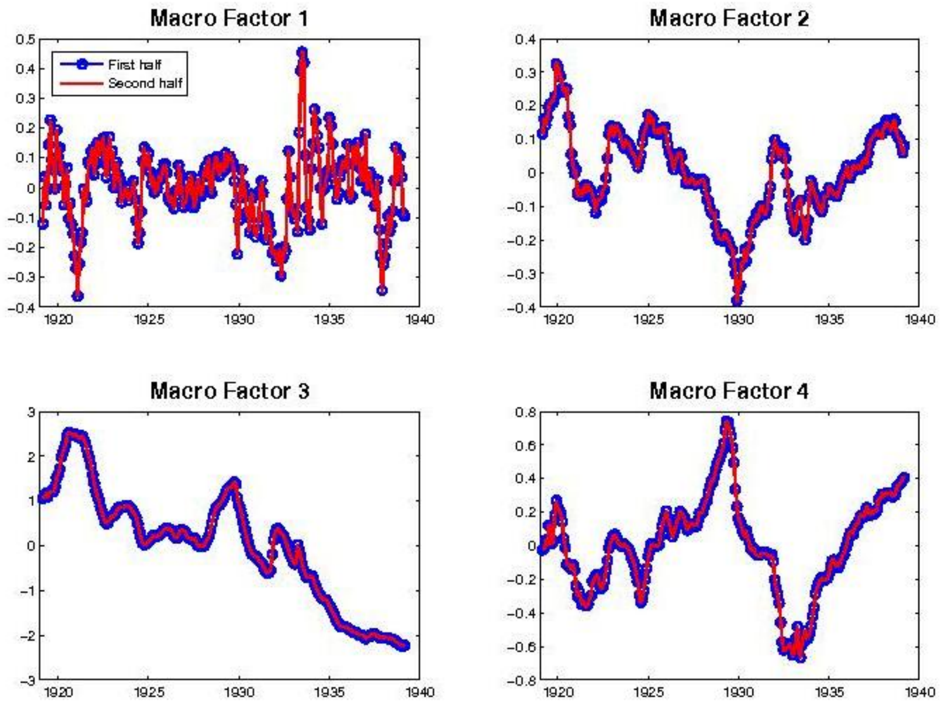
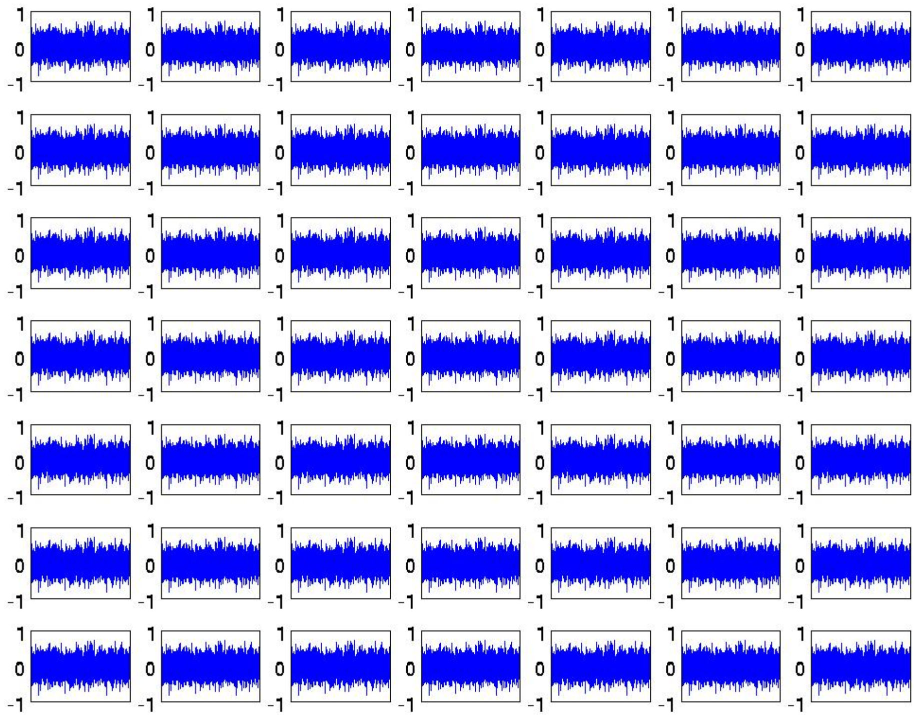


Figure 3: **Trace Plot for selected elements in $\mathbf{B}^{\mathbf{T}}$**

Trace plot of state coefficients. Graphical monitoring of convergence along the sample sampled Markov chain.



D.2 The Surprise Component of Monetary Policy

Figure 4: IRF and FEVD to Monetary Policy Shock, DR model, Full Sample Period: 1919:02 - 1939:02, identified by sign restrictions

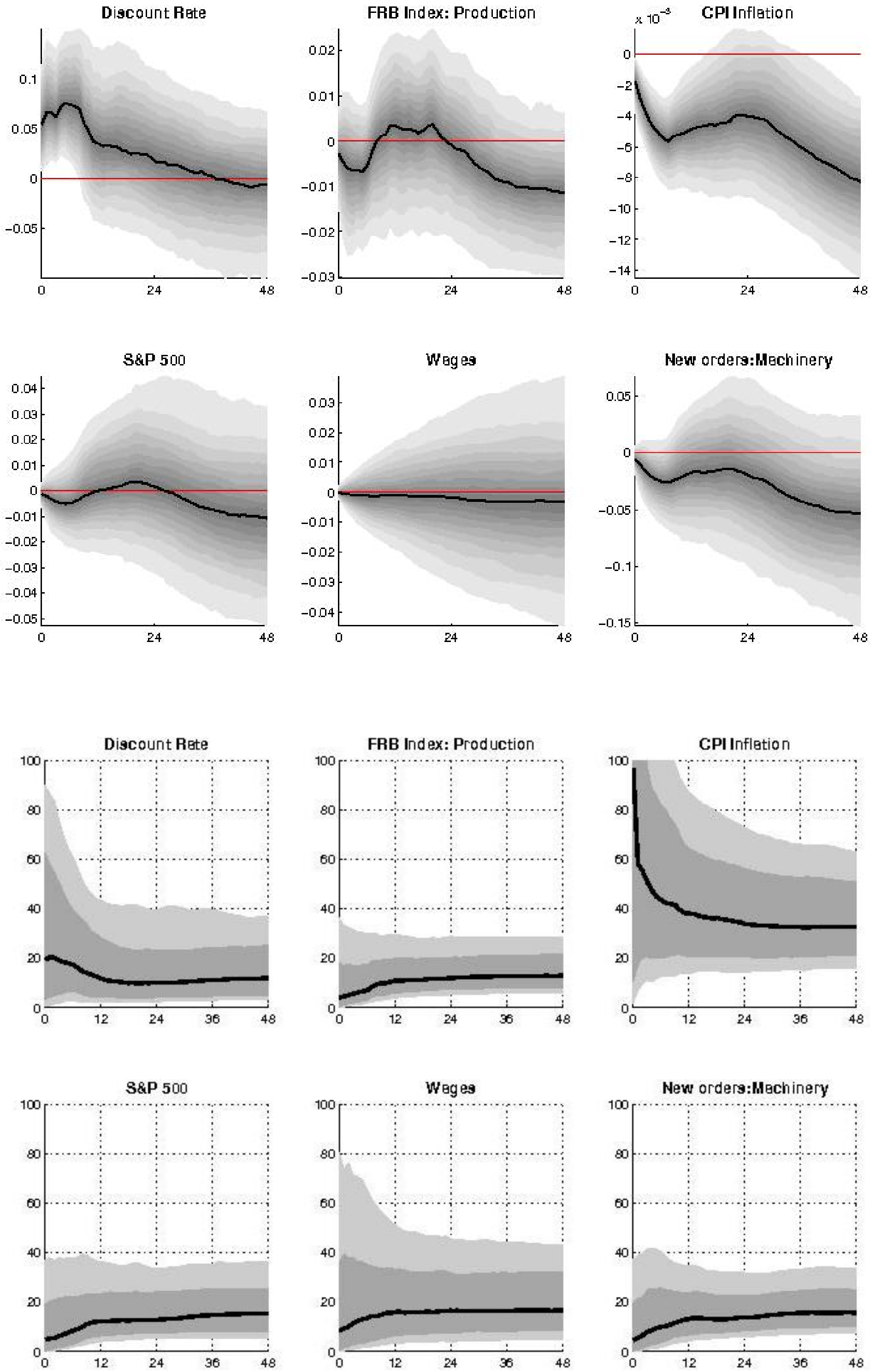


Figure 5: IRF and FEVD to Monetary Policy Shock, CommPR model, Full Sample Period: 1919:02 - 1939:02, identified by sign restrictions

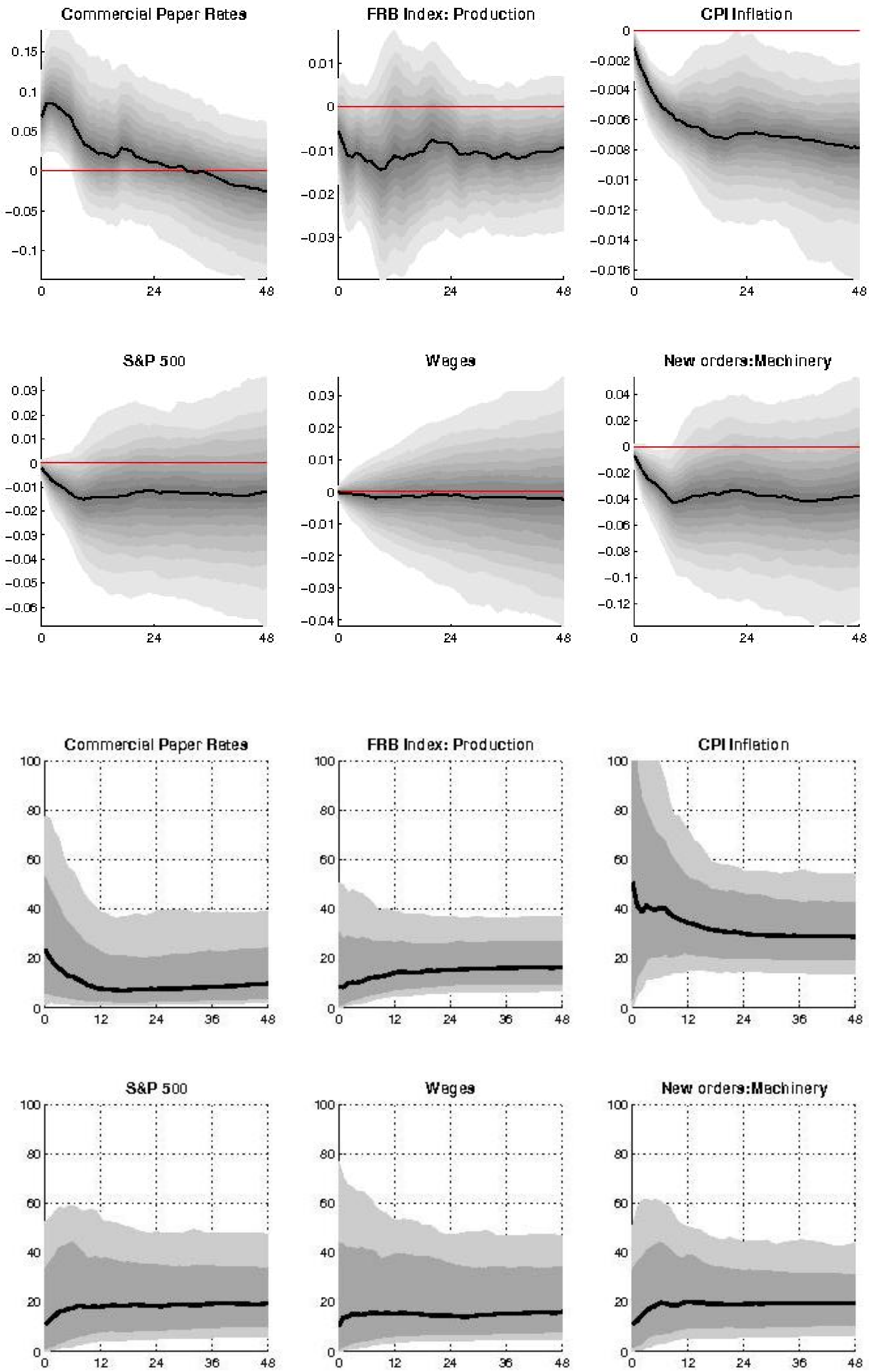


Figure 6: IRF and FEVD to Monetary Policy Shock, M0 model, Full Sample Period: 1919:02 - 1939:02, identified by sign restrictions

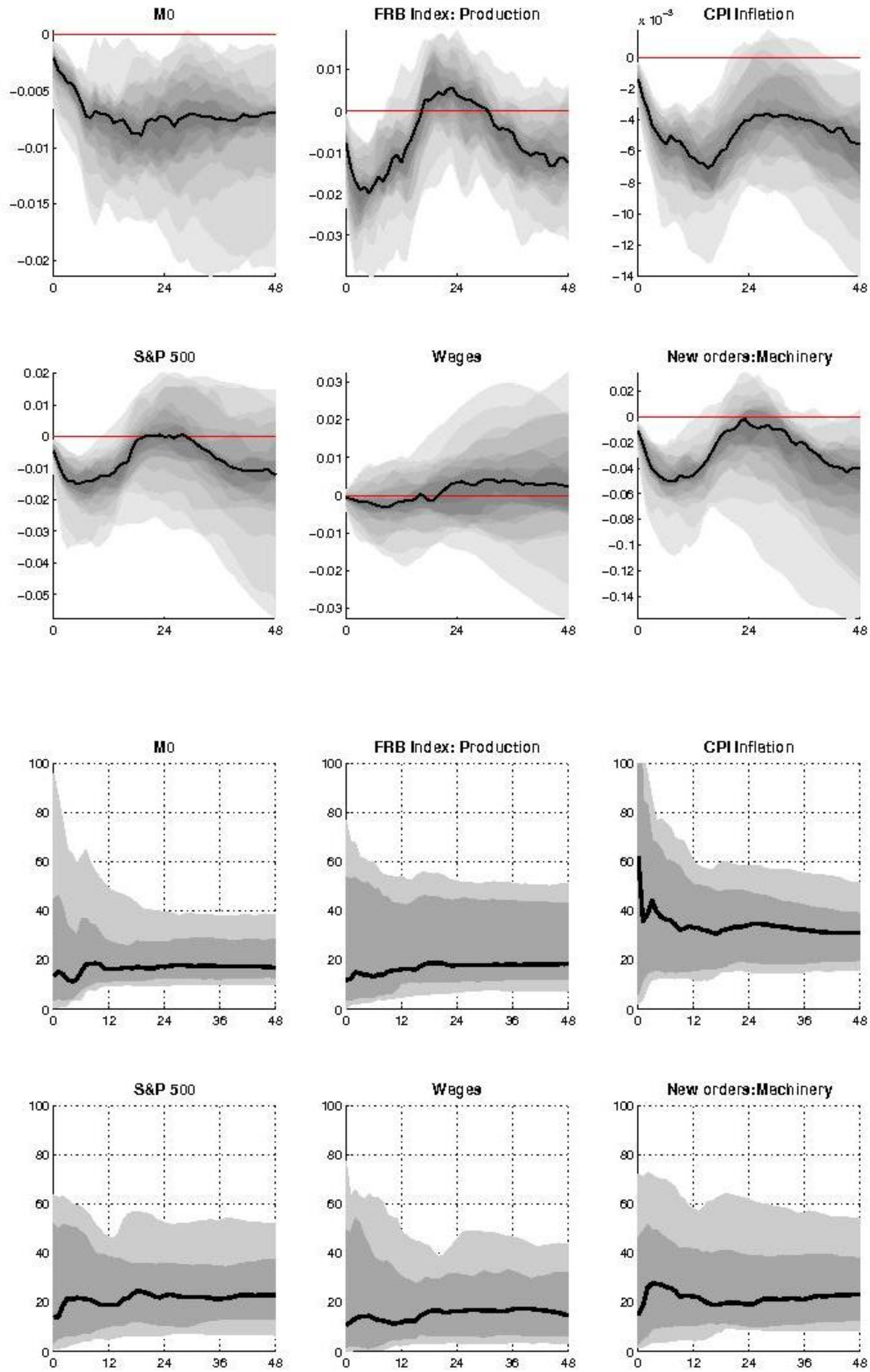


Figure 7: IRF and FEVD to a **Monetary Policy Shock** in the **M1 model** for **Fullsample Period: 1919:02 - 1939:02** identified with sign restriction

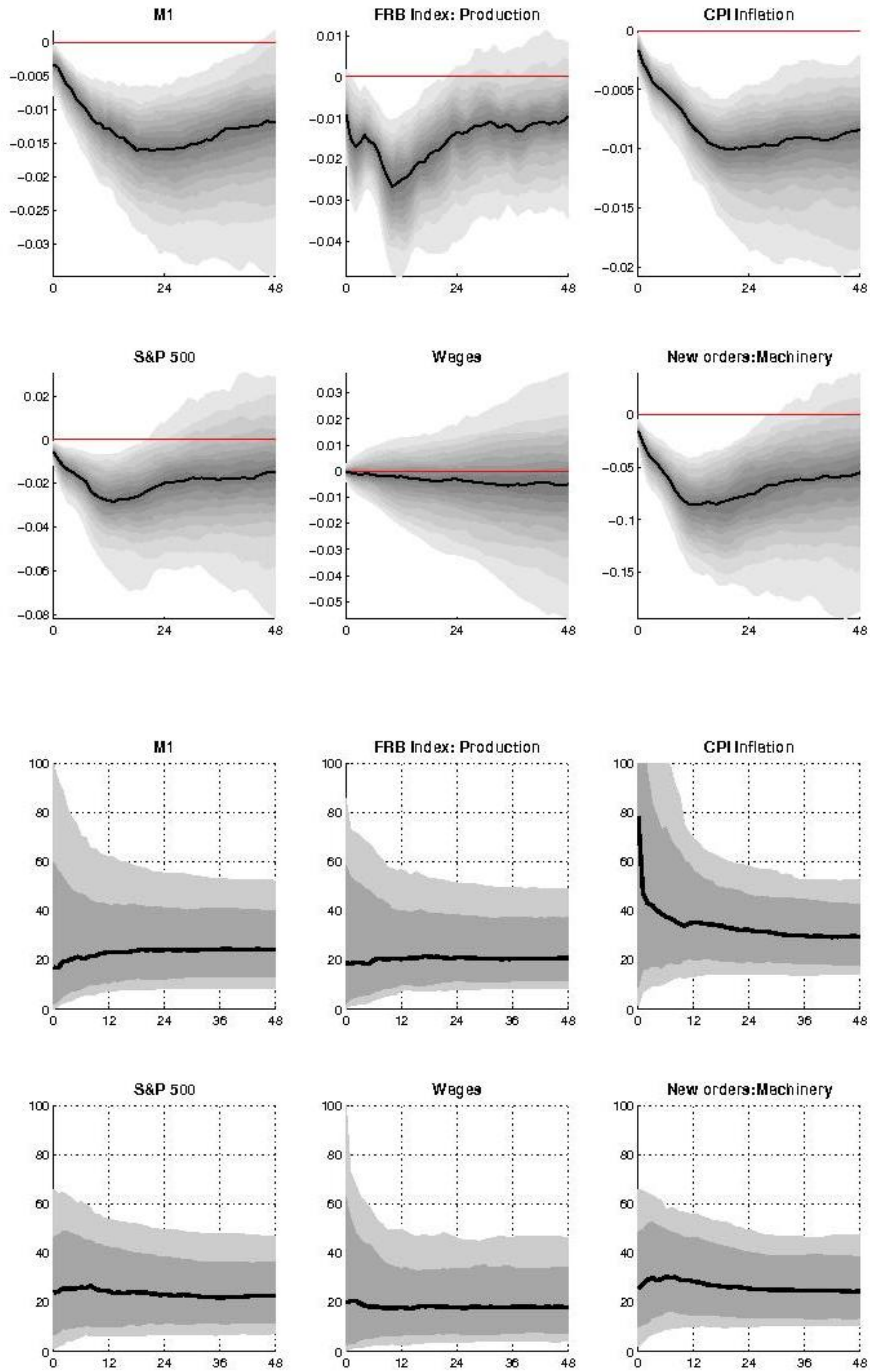
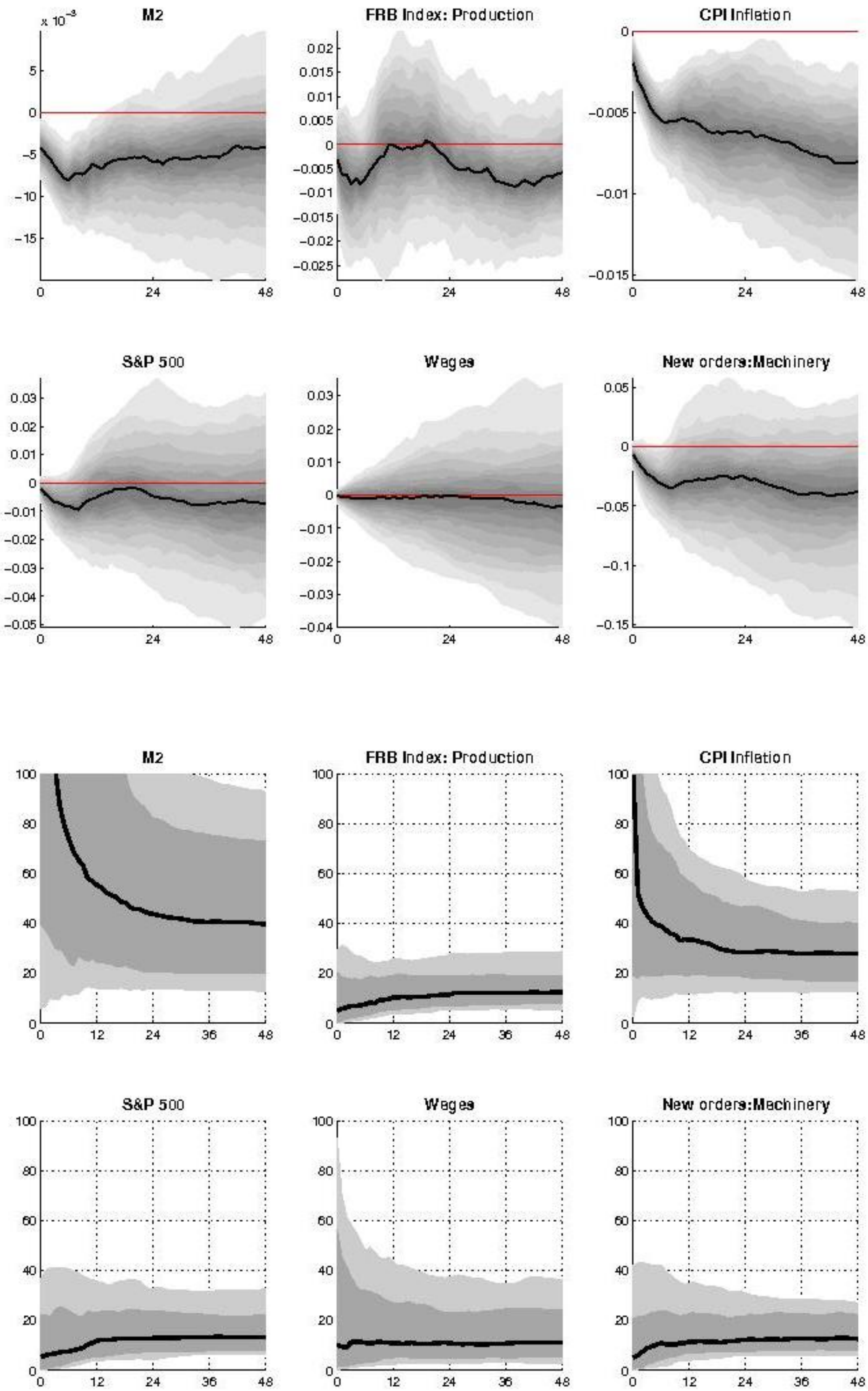


Figure 8: IRF and FEVD to a **Monetary Policy Shock** in the **M2 model** for **Fullsample Period: 1919:02 - 1939:02** identified with sign restriction



D.3 Identifying the Monetary Policy Reaction Function

Figure 9: IRF and FEVD to an Aggregate Supply Shock, DR model, Full Sample Period: 1919:02 - 1939:02, identified by sign restrictions

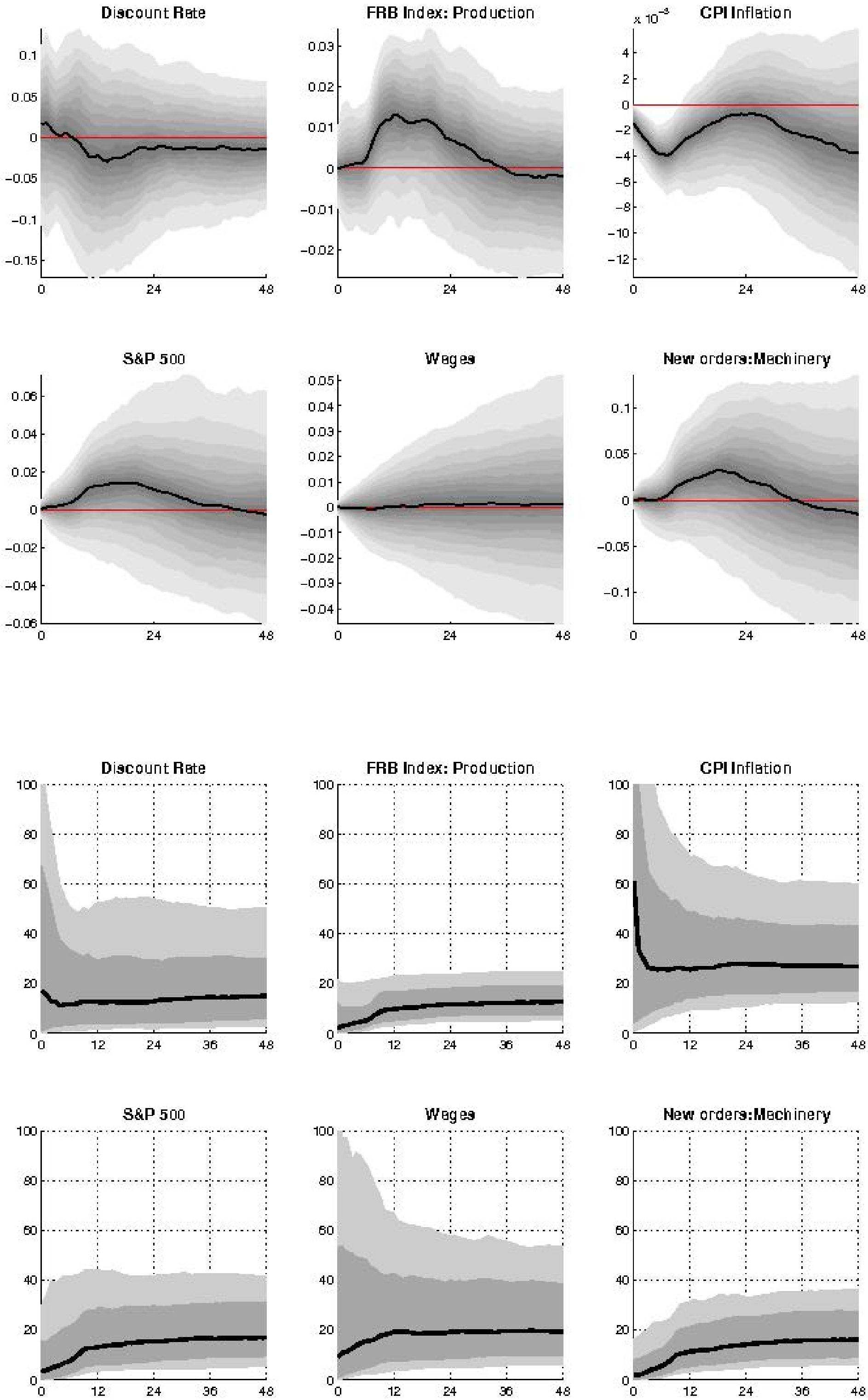


Figure 10: IRF and FEVD to an Aggregate Supply Shock, CommPR model, Full Sample Period: 1919:02 - 1939:02, identified by sign restrictions

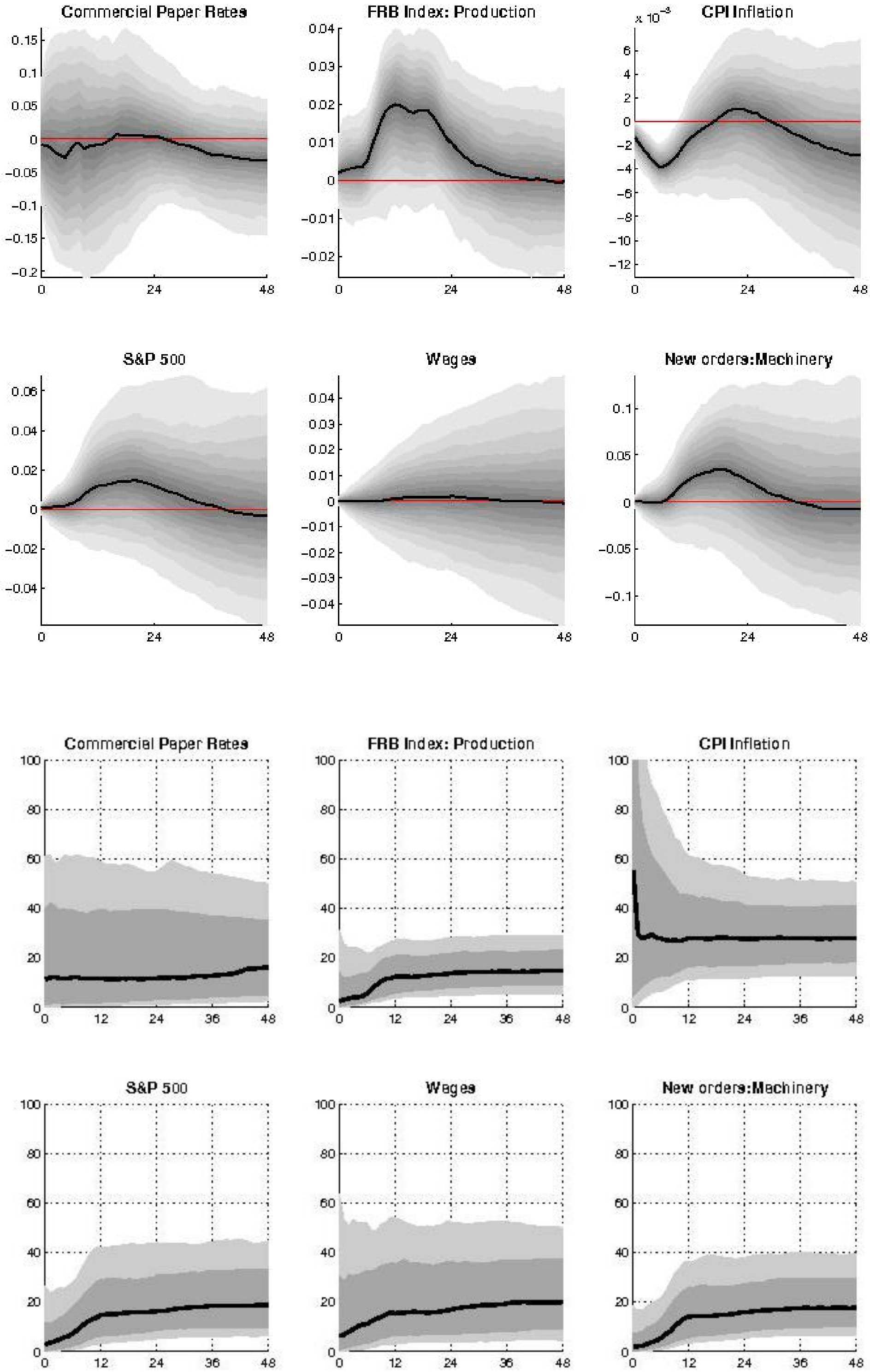


Figure 11: IRF and FEVD to an Aggregate Supply Shock, M0 model, Full Sample Period: 1919:02 - 1939:02, identified by sign restrictions

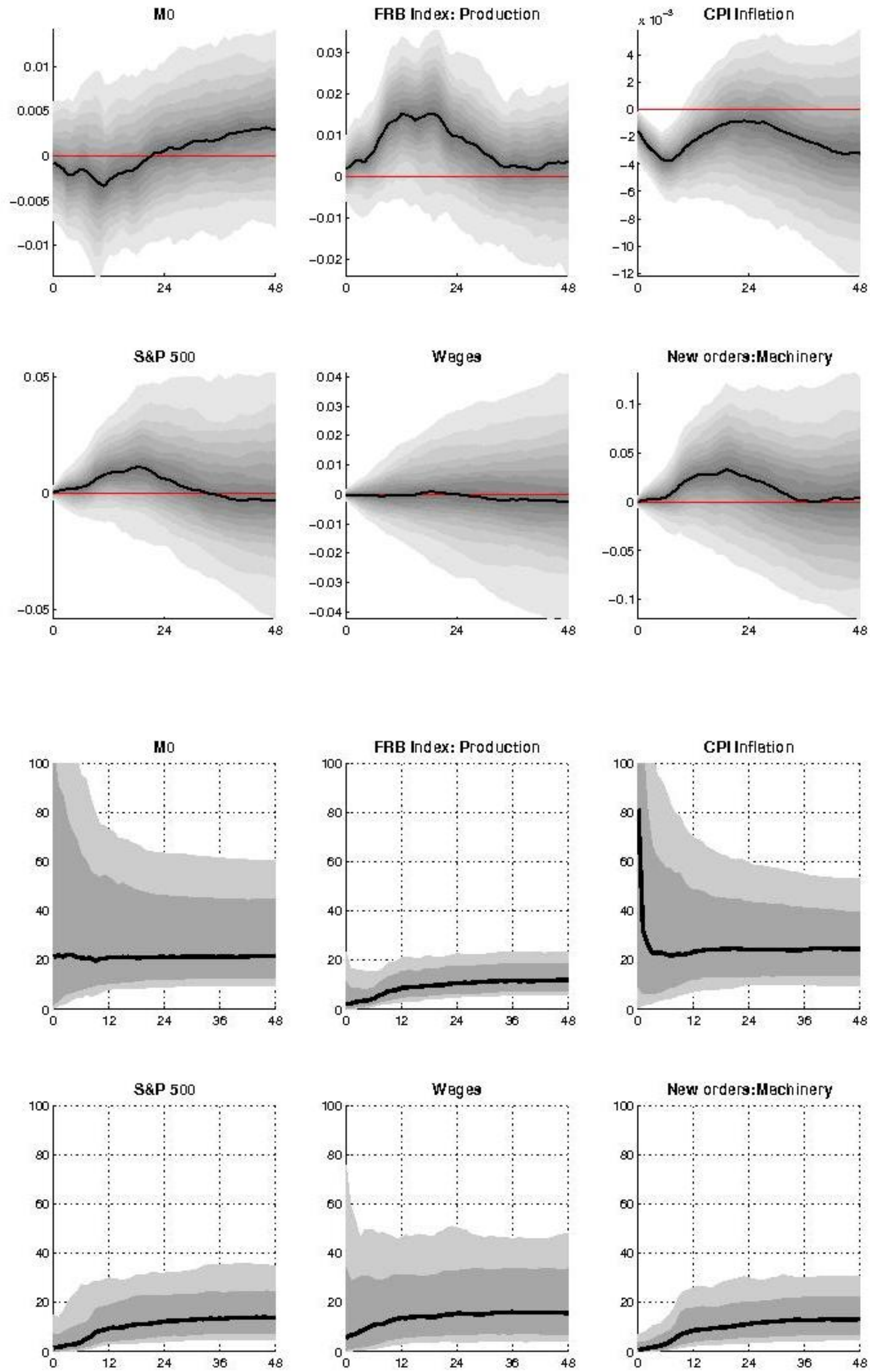


Figure 12: IRF and FEVD to an Aggregate Supply Shock, M1 model, Full Sample Period: 1919:02 - 1939:02, identified by sign restrictions

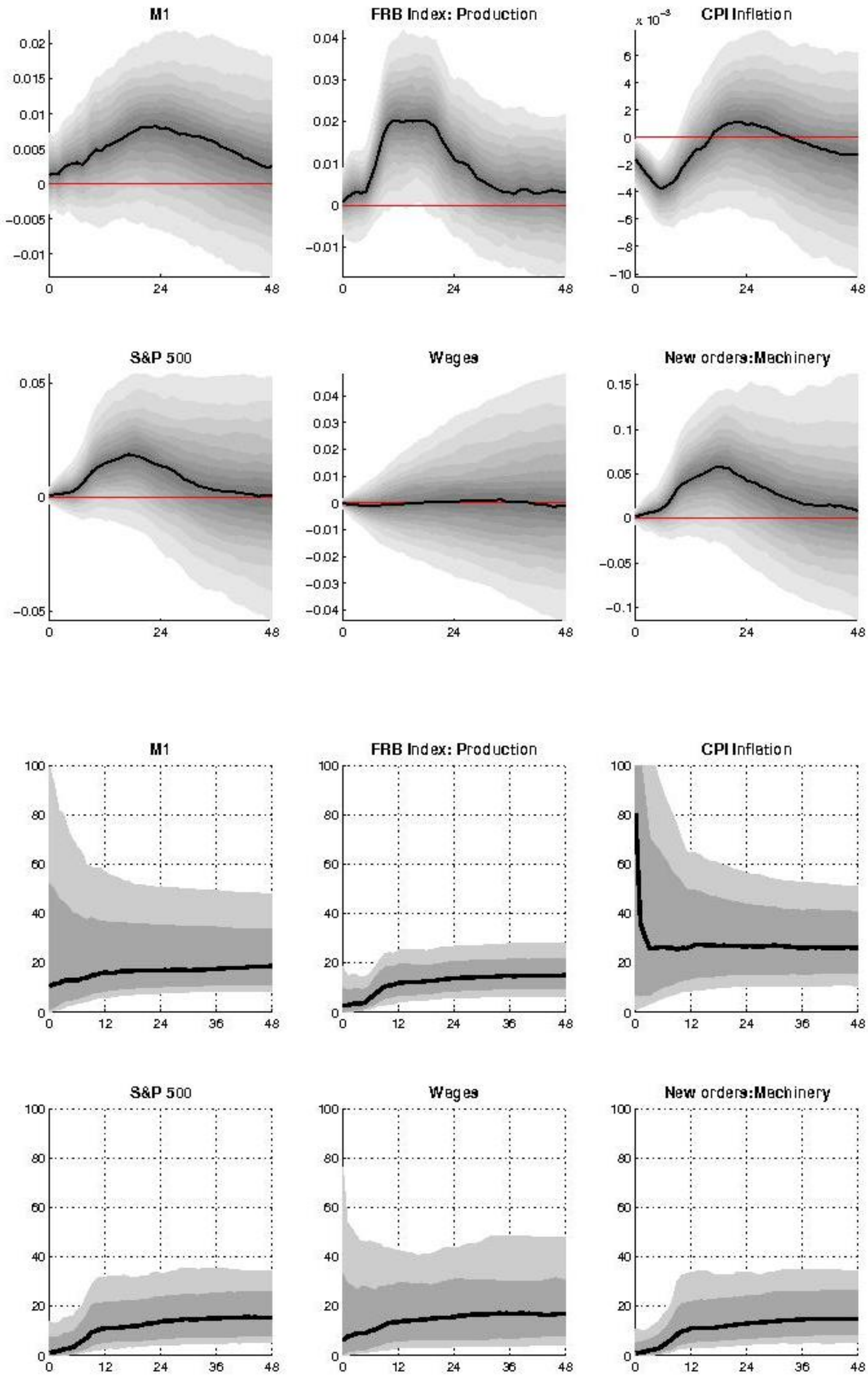
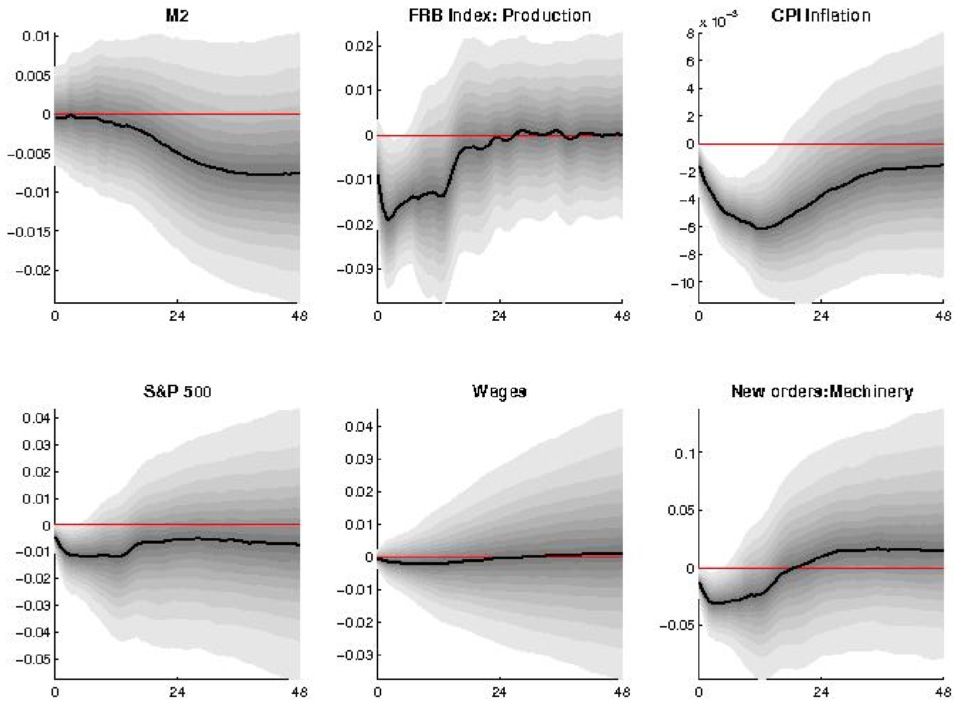


Figure 13: IRF and FEVD to an Aggregate Supply Shock, M2 model, Full Sample Period: 1919:02 - 1939:02, identified by sign restrictions



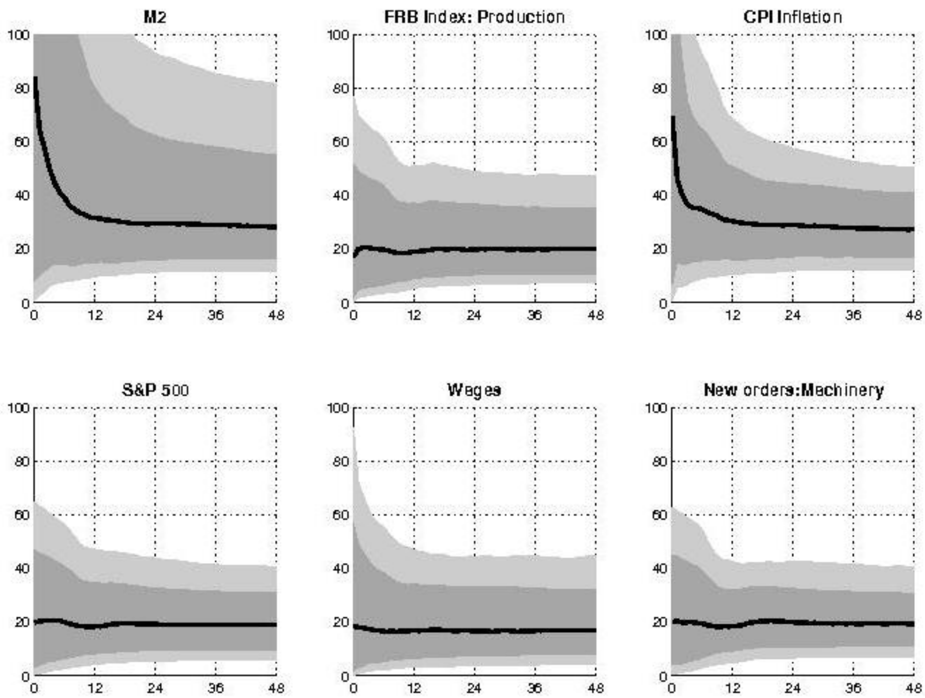


Figure 14: IRF and FEVD to an Aggregate Demand Shock, DR model, Full Sample Period: 1919:02 - 1939:02, identified by sign restrictions

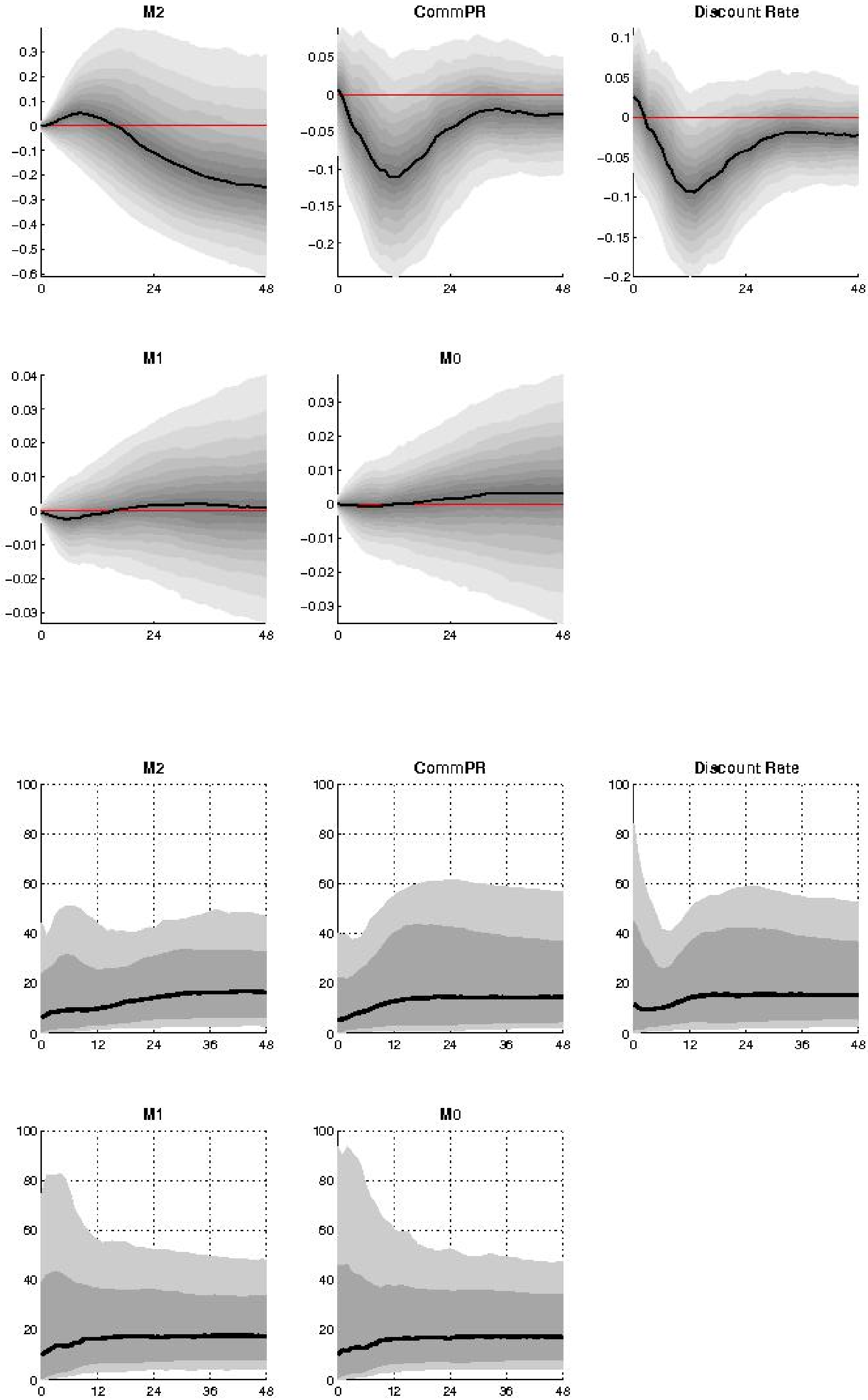


Figure 15: IRF and FEVD to an Aggregate Demand Shock, CommPR model, Full Sample Period: 1919:02 - 1939:02, identified by sign restrictions

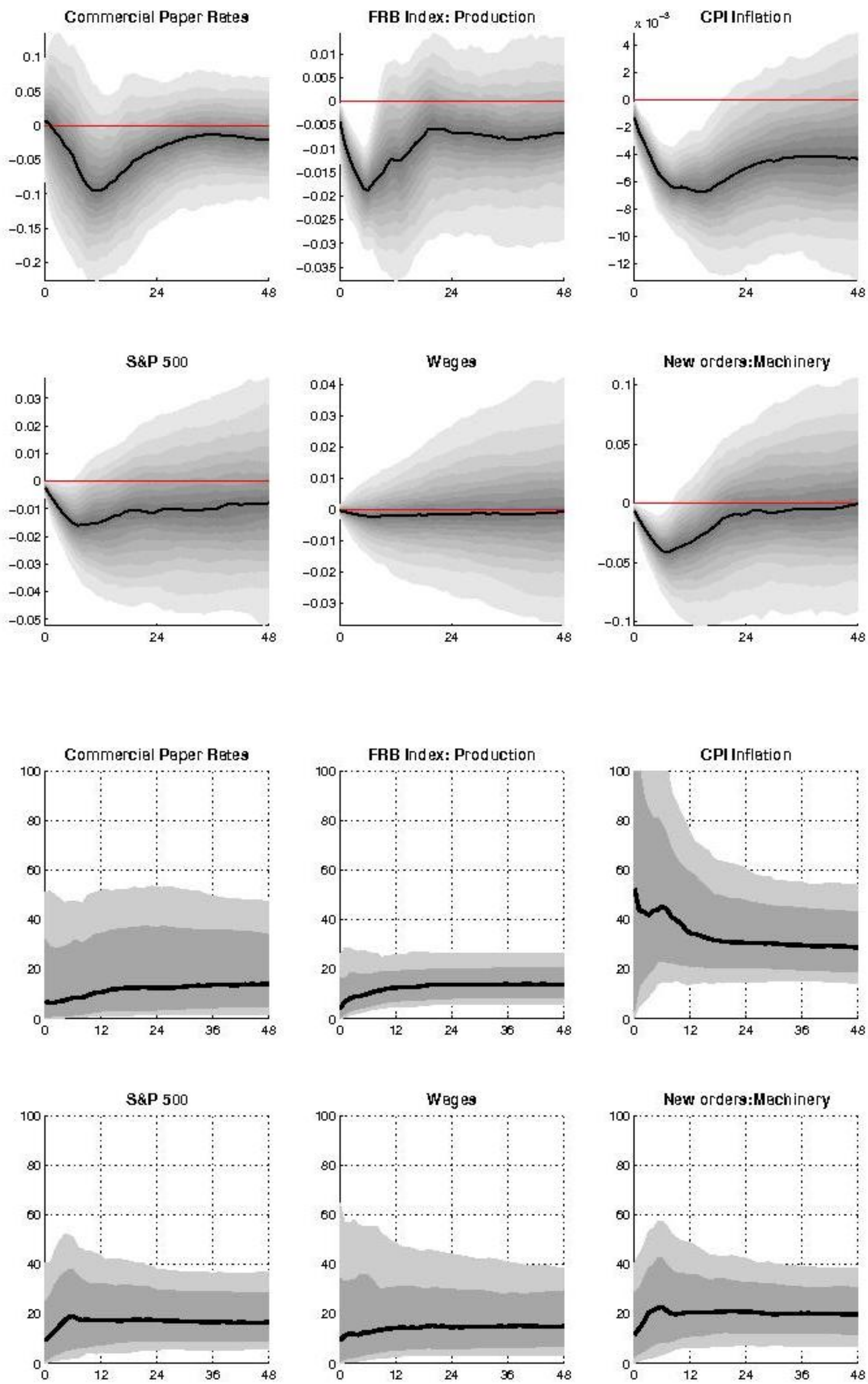


Figure 16: IRF and FEVD to an Aggregate Demand Shock, M0 model, Full Sample Period: 1919:02 - 1939:02, identified by sign restrictions

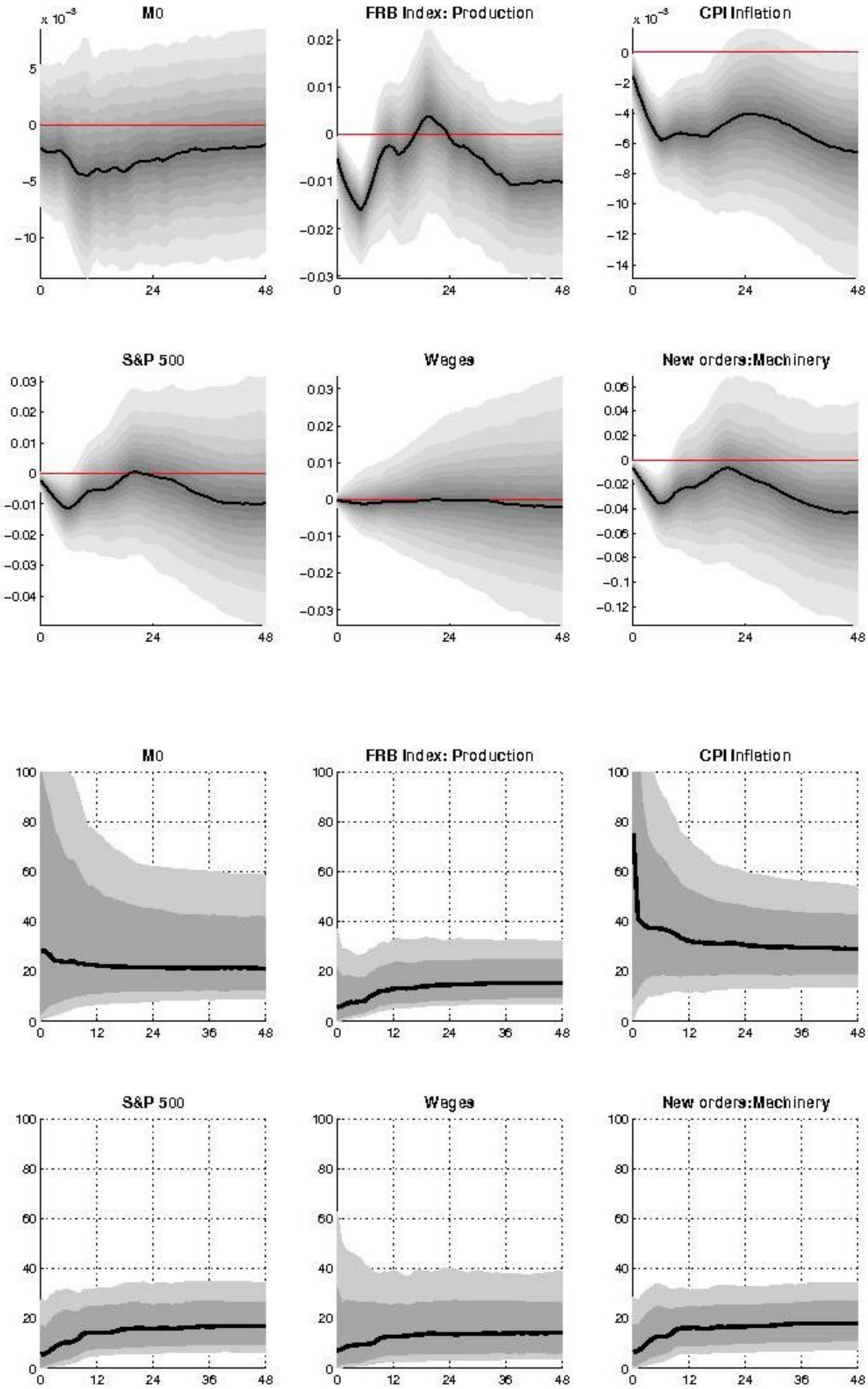


Figure 17: IRF and FEVD to an Aggregate Demand Shock, M1 model, Full Sample Period: 1919:02 - 1939:02, identified by sign restrictions

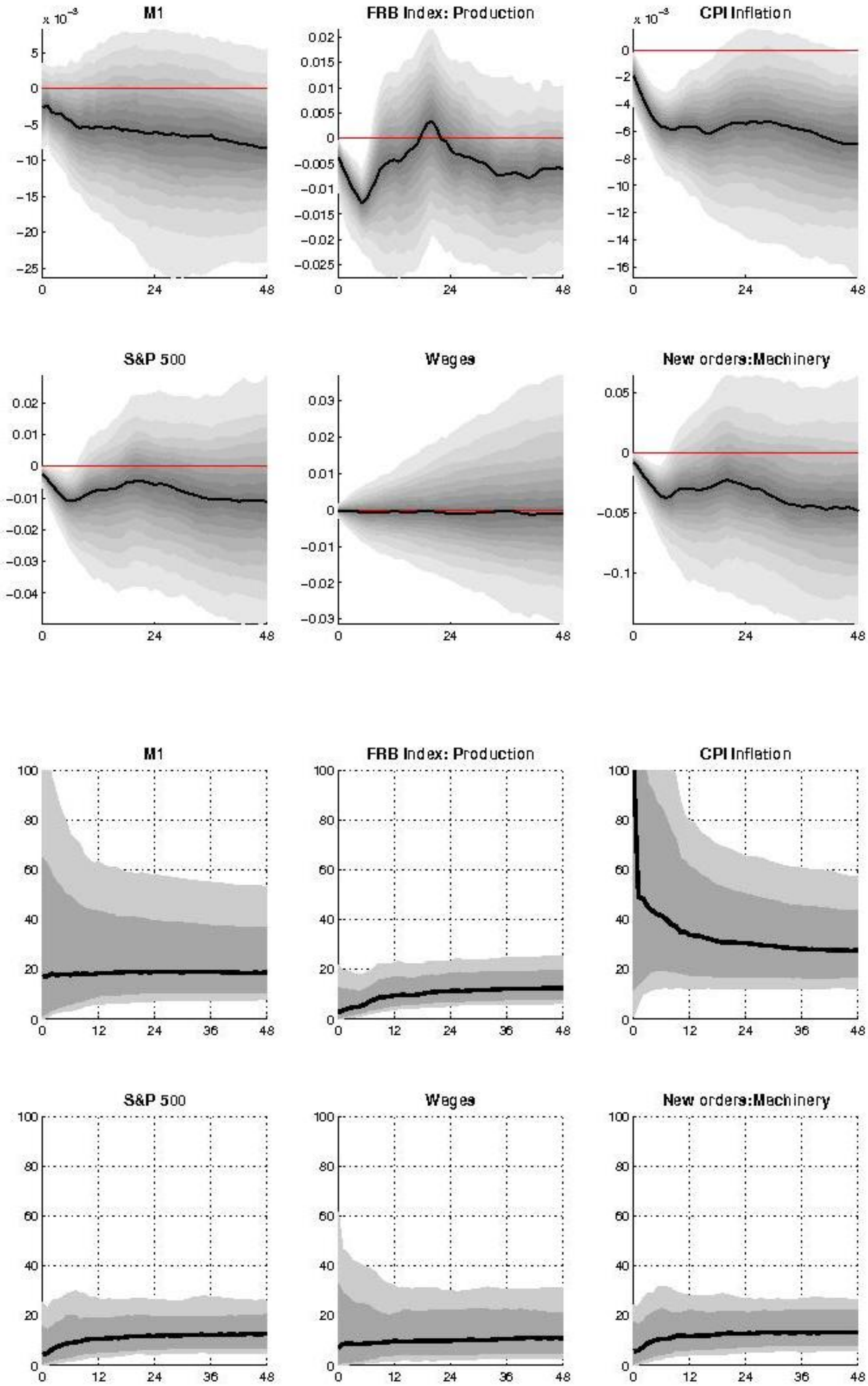


Figure 18: IRF and FEVD to an Aggregate Demand Shock, M2 model, Full Sample Period: 1919:02 - 1939:02, identified by sign restrictions

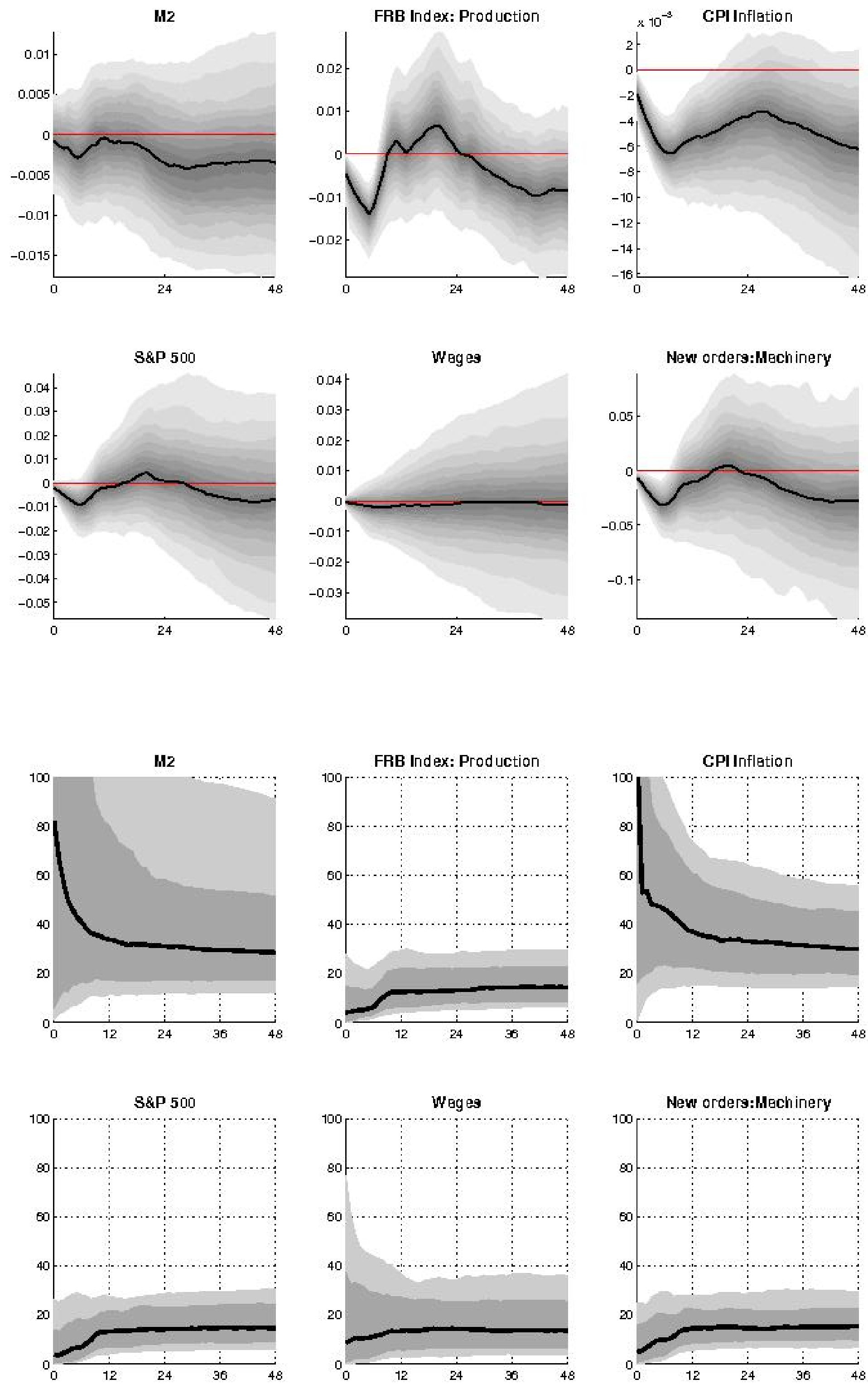


Figure 19: **Conditional Forecasts WITHOUT policy instrument**

Forecasting WITHOUT Monetary Policy Instruments

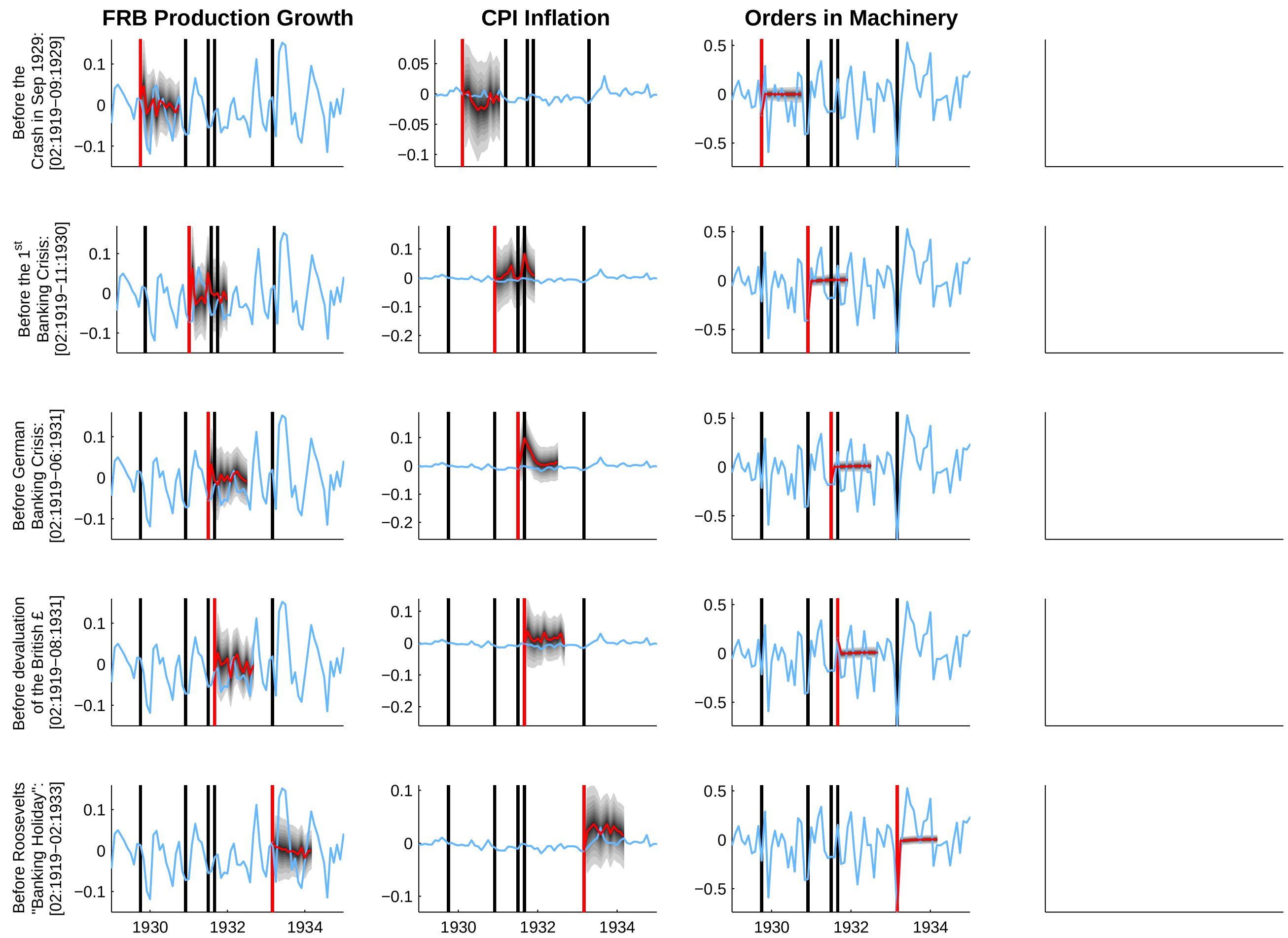


Figure 20: **Conditional Forecasts: Commercial Paper Rate Model**

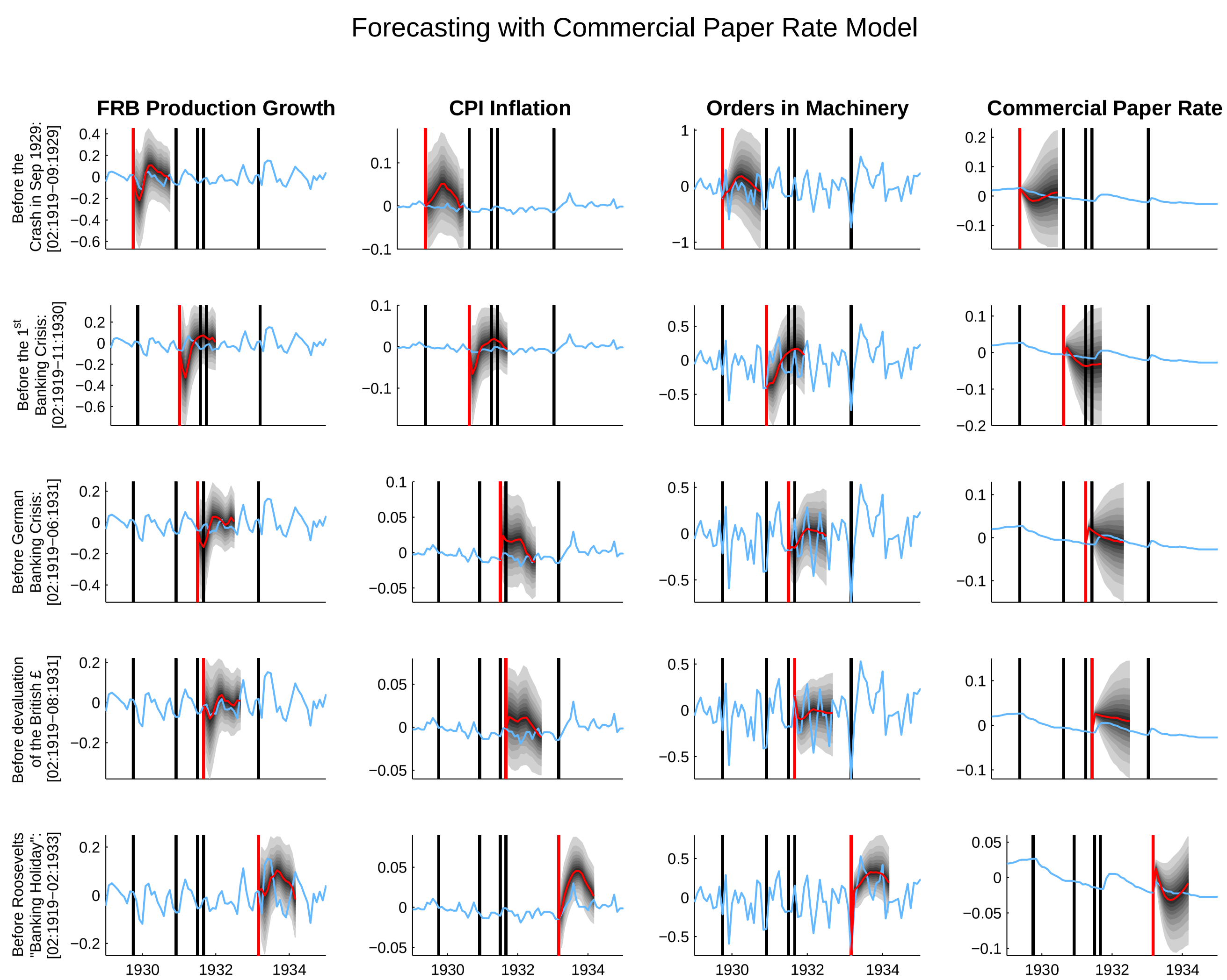


Figure 21: **Conditional Forecasts: Discount Rate Model**

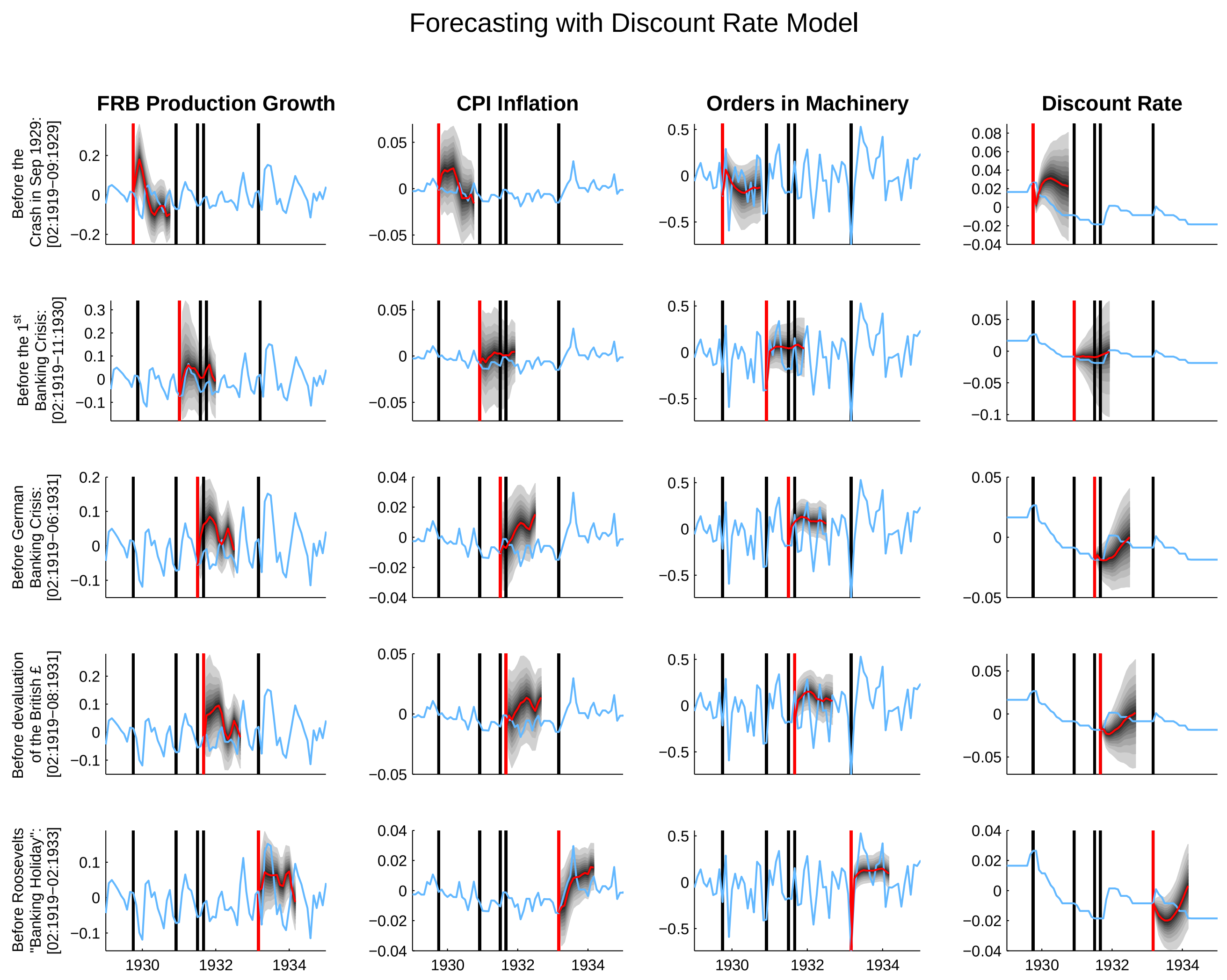


Figure 22: **Conditional Forecasts: M0 Model**

Forecasting with Monetary Base Model

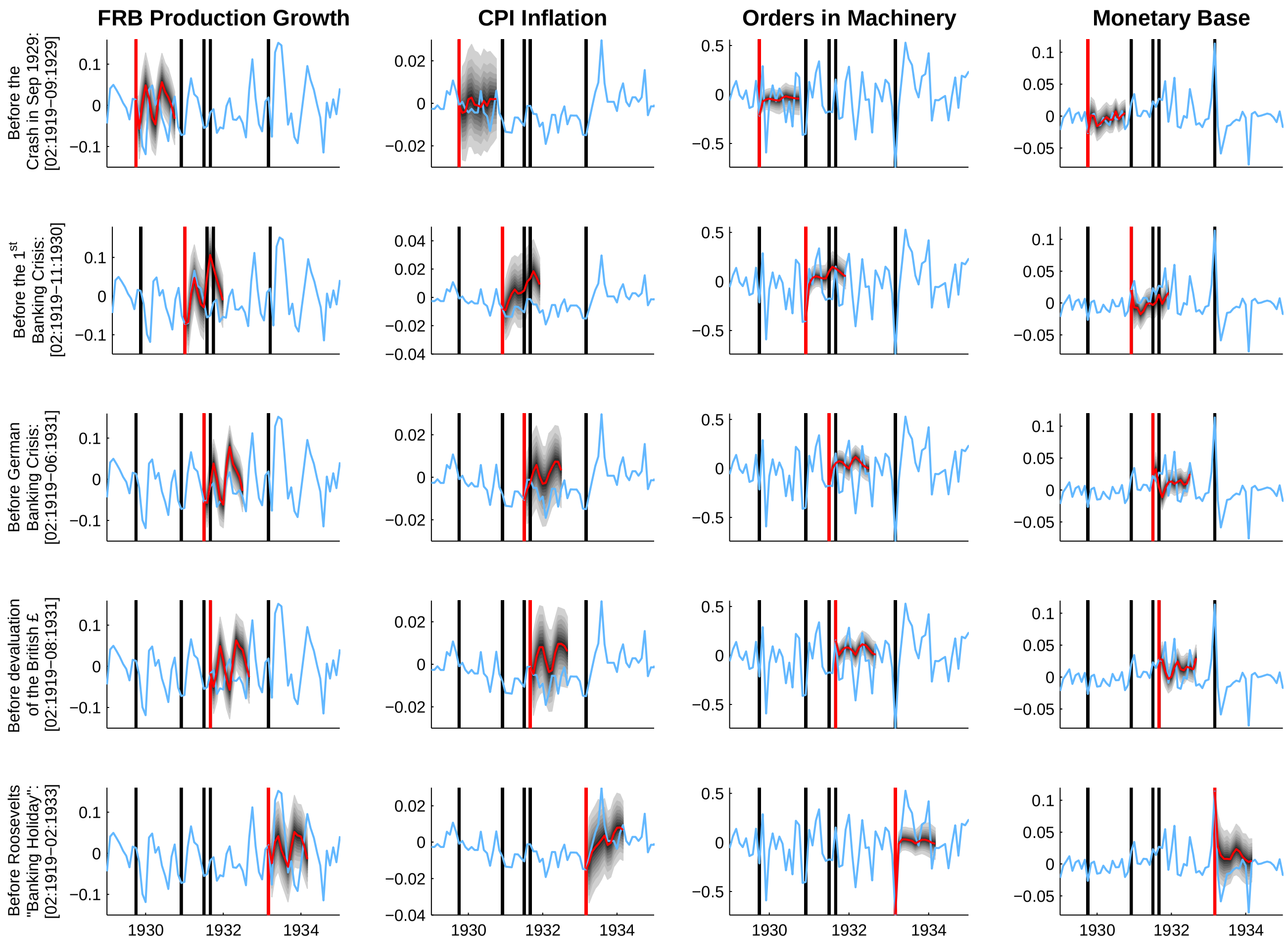


Figure 23: **Conditional Forecasts: M1 Model**

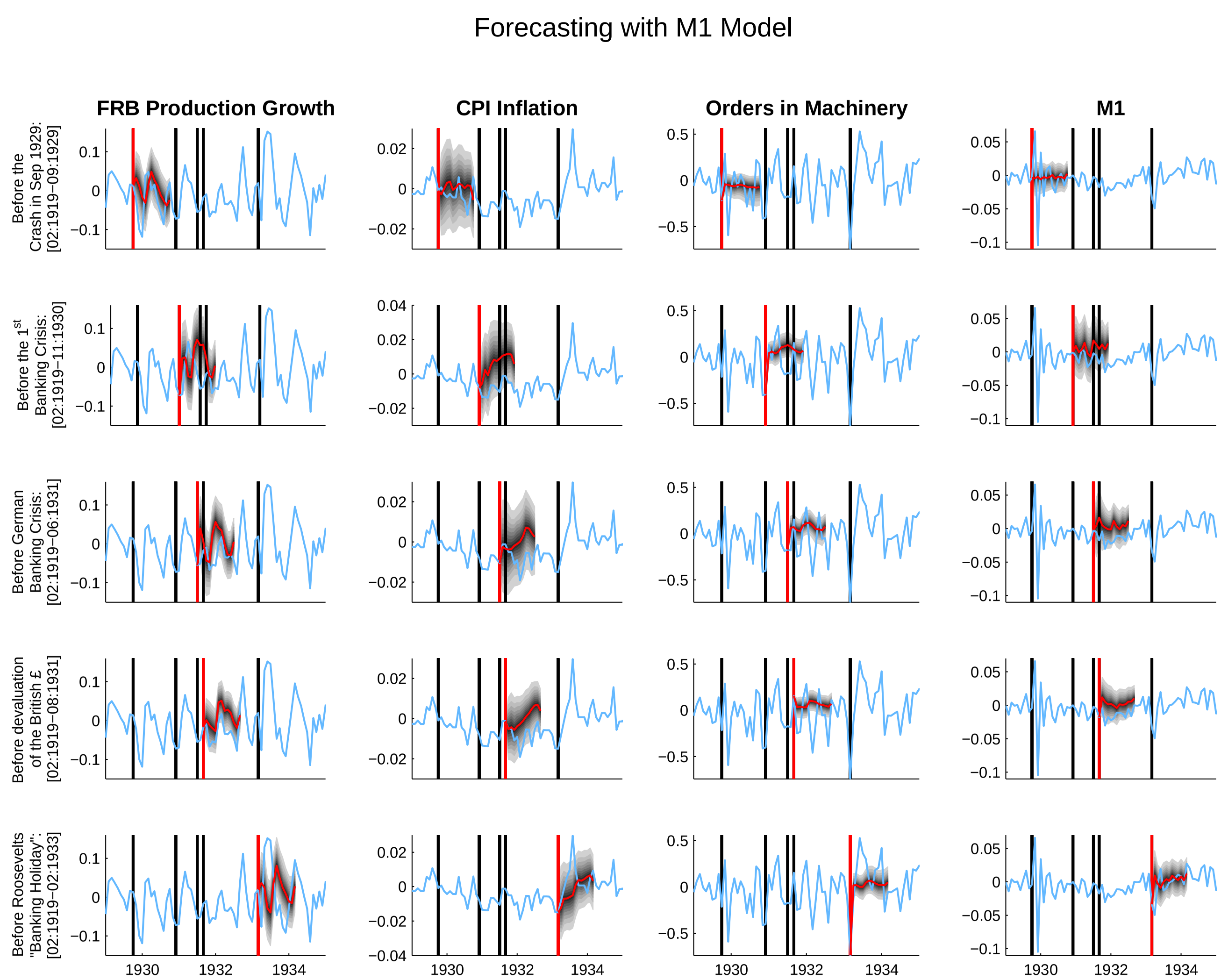
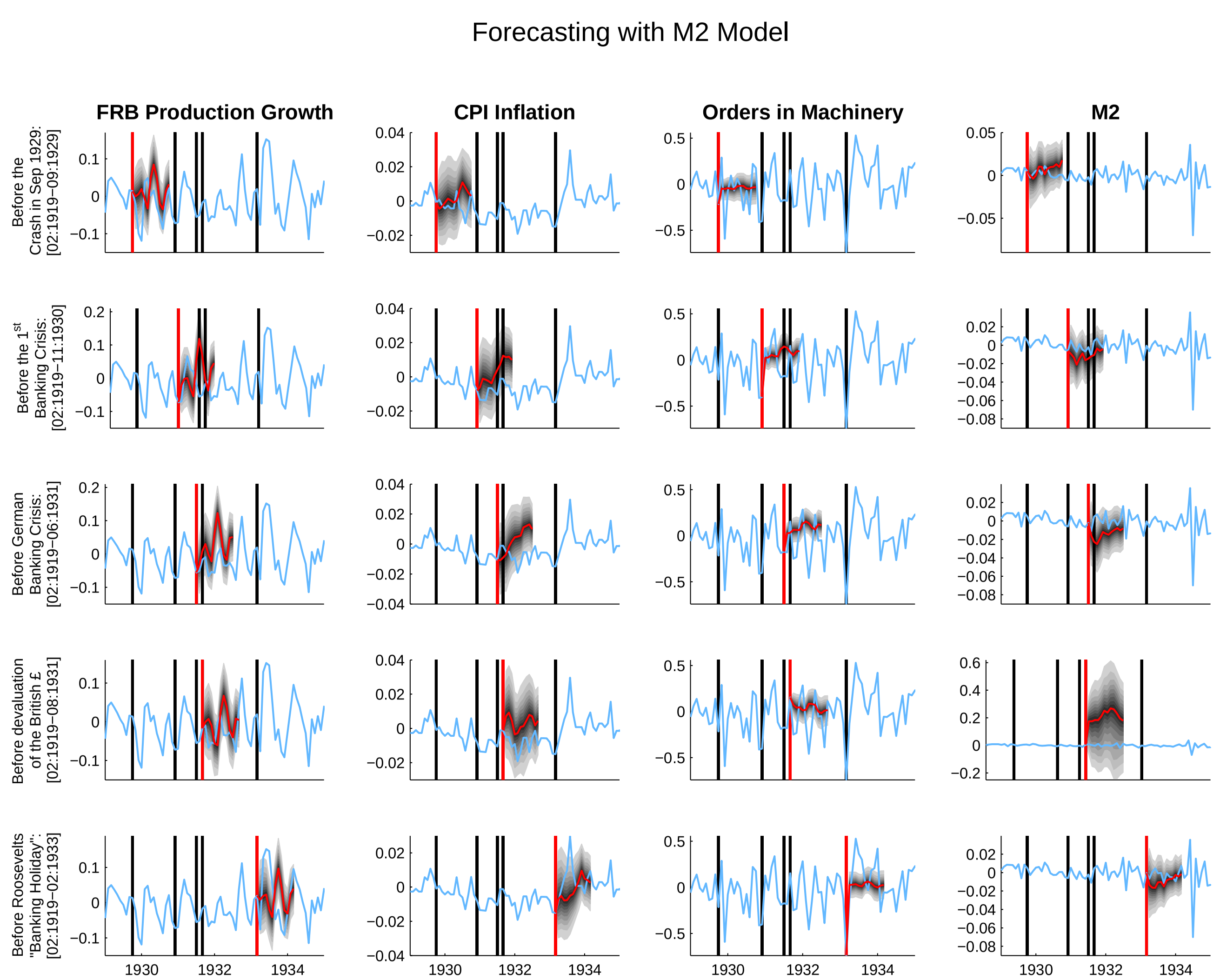


Figure 24: **Conditional Forecasts: M2 Model**



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