Credit Conditions and the Effects of Economic Shocks: Amplification and Asymmetries

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Abstract

In this paper we address three empirical questions related to credit conditions. First, do they change the dynamic interactions of economic variables? Second, do they enlarge the effects of economic shocks? Third, do they generate asymmetries in the effects of economic shocks? To answer these questions, we introduce endogenous regime switching in the parameters of a large Multivariate Autoregressive Index (MAI) model, where all variables react to a set of observable common factors. We develop Bayesian estimation methods and show how to compute responses to common structural shocks. We find that credit conditions do act as a trigger variable for regime changes. Moreover, demand and supply shocks are amplified when they hit the economy during periods of credit stress. Finally, good shocks seem to have more positive effects during stress time, in particular on unemployment.

Keywords: Credit conditions, shock amplification, asymmetric effects, Multivariate Autoregressive Index models, Smooth Transition, Bayesian VARs, Large datasets, Structural Analysis.

J.E.L. Classification: E32, C11, C55

1 Introduction

There is by now substantial empirical evidence on the interaction of credit conditions and the macroeconomy. Several recent studies focused on corporate bond spreads, which tend to widen in stress periods, e.g., Gilchrist and Zakrajsek (2012), Faust, Gilchrist, Wright and Zakrajsek (2013) and Lopez-Salido, Stein and Zakrajsek (2017). A common result is that an increase in credit spreads leads to a decline in economic activity, e.g., Gilchrist, Yankov and Zakrajsek (2009). Lopez-Salido et al. (2017) describe how mean reversion in credit spreads due to sentiment implies that low credit spreads are followed two years later by widening spreads and a decline of economic activity. These empirical links between credit spreads and economic activity are supported by theoretical results, often presented in the context of DSGE models with financial frictions (Bernanke and Gertler, 1989; Kiotaki and Moore, 1997). These models suggest that financial conditions may lead to amplification effects of negative shocks, that is, to nonlinearities.

Our paper contributes to the empirical literature. Specifically, we address three questions related to credit conditions. First, do they change the dynamic interactions of economic variables? Second, do they amplify the effects of economic shocks? Third, do they generate sign asymmetries in the effects of economic shocks?

From an econometric point of view, to answer these questions we need a time-varying parameter model. We develop a particular Smooth Transition Vector Autoregressive (ST-VAR) model, which is simple, intuitive and computationally feasible. Parameters changes in a ST-VAR can be led either by an observable indicator (Weise, 1999), a combination of indicators (Galvao and Marcellino, 2014), or an unobserved factor (Galvao and Owyang, 2016). ST-VAR models have been often used to study asymmetries in the responses to monetary policy shocks (Weise, 1999), fiscal shocks (Auerback and Gorodnichenko, 2012) and financial shocks (Galvao and Owyang, 2016). ST-VAR models nest Threshold VAR models, where parameter time variation is abrupt, which were applied, e.g., by Balke (2000) to consider credit as a nonlinear propagator of shocks.

ST-VAR models are normally estimated for a small set of endogenous variables (the examples above and others in the literature consider up to 5 variables) because the characterization of the regime-dependent dynamics worsens usual dimensionality issues in VAR models (see, e.g., the recent survey by Hubrich and Terasvirta (2013)). However, larger VARs are typically needed to obtain reliable estimates of responses to shocks (Bańbura, Giannone and Reichlin, 2010;

Giannone, Lenza and Primiceri, 2015; Burnnermeier, Palia, Sastry and Sims, 2017). Moreover, the measurement of credit conditions is normally based on information from many different credit spreads, e.g., Hatzius, Hooper, Mishkin, Schoenholtz and Watson (2010). Gilchrist et al. (2009) and Galvao and Owyang (2016) employ factor augmented VAR models to deal with this dimensionality issue. We, instead, employ a novel approach that has many advantages when performing structural analysis, since it has no unobservable variables, there is only a small set of common shocks, and it can be easily extended to allow for time variation.

We start from the Multivariate Autoregressive Index (MAI) model of Reinsel (1983) and Carriero, Kapetanios and Marcellino (2016). In the MAI model, reduced rank restrictions on the matrices of the original VAR model imply that each variable is driven by (the lags of) a limited set of linear combinations of all variables, which can be interpreted as observable factors (Indexes). In this sense, MAI models are a bridge between VAR and factor models.

We introduce smooth time variation in the parameters of the conditional mean and the conditional variance of the MAI model, with one of the observable common factors (specific linear combinations of economic variables) employed as transition variable. Hence, factors are not only the common drivers of all the variables, but also the triggers of parameter time variation.

We develop Metropolis-in-Gibbs algorithms to estimate the smooth transition MAI (ST-MAI) model. We follow Lopes and Salazar (2005) and Galvao and Owyang (2016) to draw parameters of smooth transition function jointly in a Metropolis step. For the regime-conditional variance-covariance matrix, we use a variation of the inverse-Wishart proposal approach in Galvao and Owyang (2016). We use the method proposed by Carriero, Kapetanios and Marcellino (2016) to estimate factors' loadings. For the specifications with variance-covariance matrix changing with the regime, we use the triangularization method proposed by Carriero, Clark and Marcellino (2016) to be able to reduce the computational time caused by the large data dimension.

We apply the ST-MAI model to a set of 20 economic and financial variables, including indicators of economic activity, prices, interest rates and credit spreads. We use four factors: real, nominal, monetary and credit.

We use the BIC to compare ST-MAI specifications with each of these four factors as transition variable. The BIC clearly selects the credit factor as the trigger of parameter time variation. In the resulting model, the threshold for low/high stress periods is endogenously determined, as well as the timing of the regimes (in contrast to Aikman, Lehner, Liang and Modugno (2017)). The identified periods of low/high stress are in line with common wisdom and are correlated with the NBER business cycle chronology. Hence, to answer our first question, we do find that credit conditions change the dynamic interactions of economic variables.

Using the selected large ST-MAI model with credit factor as transition variable, we then compute (generalized) impulse response functions to demand, supply, monetary and credit shocks. We find that shocks that depress economic activity (negative demand shocks and positive supply shocks) are amplified when they hit the economy in the credit stress regime. Similarly, shocks that widen credit spreads have amplified negative effects on prices when the economy is in the credit stress regime. Hence, to answer our second question, we find substantial evidence that credit conditions can amplify the effects of economic shocks.

Finally, and in contrast to Lopez-Salido et al. (2017) who found no asymmetric effects of changes in credit spreads on GDP growth, we find that unemployment responds differently to positive and negative shocks when the model is in the credit stress regime. Shocks that decrease either prices or credit spreads have faster and stronger effects on unemployment than shocks that increase these variables. Hence, to answer our third question, we also find evidence that credit conditions can trigger asymmetric effects of economic shocks.

The remaining of the paper is organized as follows. Section 2 reviews the MAI model and then introduces the ST-MAI model. It also outlines the Bayesian estimation strategy, the shock identification approach, and a method for computation of the impulse responses. Section 3 applies the ST-MAI model to address our empirical research questions. Section 4 summarizes and concludes.

2 The Smooth Transition Multivariate Autoregressive Index Model

This section presents the Smooth Transition Multivariate Autoregressive Index (ST-MAI) model, to be used to study amplification and asymmetries in the effects of economic shocks. After introducing the model, we consider (Bayesian) estimation, specification issues, and computation of impulse responses to common structural shocks,

2.1 The ST-MAI model

Let us assume that an $N \times 1$ vector of variables Y_t evolves as a VAR(p):

$$Y_t = \sum_{u=1}^{p} C_u Y_{t-u} + \varepsilon_t, \tag{1}$$

with $\varepsilon_t \sim i.i.d.(0, \Sigma)$, $t = 1, ..., T$, and we omit deterministic terms just for notational convenience. The number of the VAR(p) parameters grows proportionally to N^2, becoming quickly larger than the sample size T. However, economic theory and empirical observation suggest that many economic variables tend to move together, being driven by a limited number of key structural shocks, related, for example, to productivity, financial conditions or economic policy. Formally, this suggests to impose a set of reduced rank restrictions on the C_u matrices in (1), decomposing each of them into $C_u = A_u B_0$, where each A_u is $N \times R$, B_0 is $R \times N$, and $u = 1, .., p$. The resulting specification, labeled Multivariate Autoregressive Index (MAI) model by Reinsel (1983) and Carriero, Kapetanios and Marcellino (2016), can be written as:

$$Y_t = \sum_{u=1}^{p} A_u B_0 Y_{t-u} + \varepsilon_t, \tag{2}$$

or

$$Y_t = \sum_{u=1}^{p} A_u F_{t-u} + \varepsilon_t, \tag{3}$$

where

$$F_t = B_0 Y_t. \tag{4}$$

The R variables in F_t can be considered as observable factors (Indexes), driving all the variables. It can be easily shown that F_t follows itself a VAR(p), driven by R shocks, $B_0 \varepsilon_t$. As R is generally much smaller than N, the MAI(p) model is much more parsimonious than the VAR(p), with a total of NRp instead of $N^2 p$ parameters in the conditional mean. This makes it computationally feasible to extend it to allow for time variation in the parameters even when N is large.

Assume now that the parameters $A_1, ..., A_p$ change smoothly with the regime. Hence, a smooth transition MAI model is:

$$Y_t = \sum_{u=1}^{p} A_u F_{t-u} + \sum_{u=1}^{p} \Pi_t(\gamma, c, x_{t-1}) D_u F_{t-u} + \varepsilon_t, \tag{5}$$

where $\Pi_t(\gamma, c, x_{t-1})$ is a logistic function, x_t is the transition variable, c is the threshold, and γ is the smoothing parameter. The model implies that if the transition variable x_{t-1} is large in comparison with the threshold c, the value of the scalar $\Pi_t(\gamma, c, x_{t-1})$ is not far from 1, and the coefficients for lag u are $(A_u + D_u)$. If instead x_{t-1} is lower than the threshold, $G_t(\gamma, c, x_{t-1})$ approximates 0, and the coefficients are A_u. This means that D_u measures the difference in conditional mean dynamic between regimes. When the smoothing parameter γ is large, the transition function resembles a step function at the threshold c, and the parameter change is abrupt.

We assume that the regimes that characterize changes in the dynamics of the endogenous variables in Y_t are driven by one of the observable factors F_t, which are also are the key drivers of fluctuations in the variables in Y_t. Hence, we have:

$$\Pi_t(\gamma, c, x_{t-1}) = \frac{1}{1 + \exp(-(\gamma/\sigma_x)(x_{t-1} - c))}, \tag{6}$$

where $x_t = f_t^{(i)}$,that is, the transition variable is one of the R observable factors (with standard deviation σ_x):

$$f_t^{(i)} = b_0^{(i)} Y_t,$$

and $b_0^{(i)}$ the i^{th} $(1 \times N)$ row of the matrix B_0, $i = 1, .., R$. We use lagged factors to trigger regime changes to avoid endogeneity problems and to allow for some time delay in the adjustment of the (macroeconomic) model dynamics. We use single factors for computational simplicity and also to determine empirically which is the key driver of regime changes.[1]

In our empirical application, where Y_t are monthly variables generally expressed as month on month growth rates, it is convenient to set the transition variable as a smoother year-on-year growth rate:

$$x_t = g_t^{(i)} = \frac{1}{12} \sum_{j=0}^{11} b_0^{(i)} Y_{t-j}, \tag{7}$$

to capture regimes with longer duration and avoid picking up outliers. A similar smoothing is used, for example, in Auerback and Gorodnichenko (2012).

We model conditional heteroskedasticity. of the $N \times 1$ vector of reduced-form disturbances

[1] A linear combination of a set of factors is a possible alternative, along the lines of Galvao and Marcellino (2014) who use a combination of variables in a small ST-VAR context.

ε_t as:

$$\begin{aligned} var(\varepsilon_t) &= \Sigma_t \\ \Sigma_t &= (1 - \Pi_t(\gamma, c, x_{t-1}))\Sigma_1 + \Pi_t(\gamma, c, x_{t-1})\Sigma_2, \end{aligned} \tag{8}$$

where $\Pi_t(\gamma, c, x_{t-1})$ is a logistic function as in (6). The specification implies that if the value of $\Pi_t(\gamma, c, x_{t-1})$ is near zero, then the variance-covariance matrix is near Σ_1, but if the value of $\Pi_t(\gamma, c, x_{t-1})$ is approximately 1, then the variance-covariance matrix is at Σ_2. As before, the transition variable x_t is the year-on-year growth equivalent of one of the factor i, $g_t^{(i)}$. Note that we have just one transition function, $\Pi_t(\gamma, c, x_{t-1})$, which implies that regime changes occur at the same time in the conditional mean and variance, as for example in Auerback and Gorodnichenko (2012).

In general when estimating large VAR models with changes in the variance-covariance matrix, many authors (Carriero, Clark and Marcellino, 2016) allow the variances to change over time (diagonal of Σ_t), while covariances (elements below the diagonal) are fixed. Our regime-dependent smooth transition specification is a parsimonious method to allow for conditional heteroskedasticity., and, as consequence, we are able to allow for covariance changes over regime. This may have important consequences for computation of responses to structural common shocks.

2.2 Estimation

To estimate the ST-MAI model, we extend the Gibbs sampling algorithm for MAI models proposed in Carriero, Kapetanios and Marcellino (2016). Following Carriero, Kapetanios and Marcellino (2016), we set:

$$Z_{t-1} = (F'_{t-1}, ..., F'_{t-p}, \Pi_t(\cdot)F'_{t-1}, ..., \Pi_t(\cdot)F'_{t-p})',$$

where $\Pi_t(\cdot) = \Pi_t(\gamma, c, x_{t-1})$, and

$$A = (A_1 ... A_p, D_1 ... D_p)',$$

such that we can write the ST-MAI model as:

$$Y_t = Z_{t-1}A + \varepsilon_t$$

$$var(\varepsilon_t) = (1 - \Pi_t(\gamma, c, x_{t-1}))\Sigma_1 + \Pi_t(\gamma, c, x_{t-1})\Sigma_2.$$

The proposed algorithm includes two Metropolis steps in a Gibbs sampling approach. The algorithm has four blocks.

The first block draws the parameters of the transition function similarly to Galvao and Owyang (2016). Conditional on previous draws of $\Sigma_1^{(s-1)}, \Sigma_2^{(s-1)}, A^{(s-1)}$ and $B_0^{(s-1)}$, we obtain a joint draw $\gamma^{(s)}, c^{(s)}$ using a Metropolis step. This assumes a gamma prior distribution for γ, and a normal distribution for c. The proposal distribution for γ is Gamma with shape parameter equal to $(\gamma^{(s-1)})^2/\Delta_\gamma$ and scale equal to $\Delta_\gamma/(\gamma^{(s-1)})$. The proposal distribution for c is a normal distribution with mean $c^{(s-1)}$ and variance Δ_c^2. Candidate threshold values are truncated such that at least 15% of the observations are in each regime based on the observed values of the transition variable $f_t^{(i)}$ or its yearly growth rate $g_t^{(i)}$. Both tuning parameters Δ_γ and Δ_c are set to achieve rejection rates of around 70%. In the empirical application, the prior for γ is set as a Gamma distribution with mean 15 and variance 1. The prior for c is a normal distribution with mean 0 and standard deviation 0.4.

The second block draws the parameters of the variance-covariance matrix. Conditional on $\gamma^{(s)}, c^{(s)}, A^{(s-1)}$ and $B_0^{(s-1)}$, we obtain draws for each $\Sigma_1^{(s)}$ and $\Sigma_2^{(s)}$ using a inverse-Wishart proposal distribution as in Galvao and Owyang (2016). The priors for the variance-covariance matrix of the first regime is set as $\Sigma_0^{-1} \sim W(C_0^{-1}, pv_0)$ where $C_0 = T{*}\underline{\Sigma}$ and $\underline{\Sigma}$ is a diagonal matrix with the variance of AR(1) processes estimated for each variable in the vector Y_t in the diagonal, and $pv_0 = N + 2$. The proposal distribution is $\Sigma_1^{-1} \sim W(C_1^{-1}, pv_1)$ with $pv_1 = pv_0 + \Delta_1 \sum_{t=1}^{T} I(f_{t-1}^{(i)} \leq c)$ [$I(.)$ is an indicator function] and $C_1 = \Delta_{\Sigma_1} \left[\sum_{t=1}^{T} e_{1t}e_{1t}'\right]$ where $e_{1t} = [1 - \Pi_t(\gamma^{(s-1)}, c^{(s-1)}, x_{t-1}^{(i,s-1)})]\varepsilon_t^{(s-1)}$ and $\varepsilon_t^{(s-1)} = (Y_t - Z_{t-1}^{(s-1)}A^{(s-1)})$. In the case of the variance-covariance of the second regime, we use the same prior as for the first regime, and the proposal distribution is $\Sigma_2^{-1} \sim W(C_2^{-1}, pv_2)$ where $pv_2 = pv_0 + \Delta_2 \sum_{t=1}^{T} I(f_{t-1}^{(i)} > c))$ and $C_2 = \Delta_{\Sigma_2} \left[\sum_{t=1}^{T} e_{2t}e_{2t}'\right]$ where $e_{2t} = [\Pi_t(\gamma^{(s-1)}, c^{(s-1)}, x_{t-1}^{(i,s-1)})]\varepsilon_t^{(s-1)}$. This Metropolis-step has a rule for rejecting a proposed draw that evaluates the new draw against the old draw using the likelihood, the prior, and the proposal weights. This is applied separately for each $\Sigma_1^{(s)}$ and

$\Sigma_2^{(s)}$, that is, $\Sigma_1^{(s)}$ is obtained conditional on $\Sigma_2^{(s-1)}$, and then $\Sigma_2^{(s)}$ is obtained conditional on $\Sigma_1^{(s)}$. The two tuning parameters Δ_{Σ_1} and Δ_{Σ_2} are set to achieve rejection rates of 70%. This differs from the random walk metropolis approach of Auerback and Gorodnichenko (2012), who draw each element of the variance-covariance matrix independently.

The third block draws the parameters of the matrix A. Conditional on $\Sigma_1^{(s)}$, $\Sigma_2^{(s)}, \gamma^{(s)}, c^{(s)}$ and $B_0^{(s-1)}$, we obtain a draw for $A^{(s)}$ using the triangularization proposed by Carriero, Clark and Marcellino (2016). The prior mean is zero for all values in A because the VAR is estimated in growth rates. The prior variance is set as:

$$
\begin{aligned}
var(A_{(l)}^{ij}) &= \frac{\lambda_1^2}{l^{\lambda_3}}\sigma_i^2 \text{ if the variable } i \text{ loads in the factor } j \text{ (for } l = 1, ...p) \\
var(A_{(l)}^{ij}) &= \frac{\lambda_1^2\lambda_2}{l^{\lambda_3}}\sigma_i^2 \text{ if the variable } i \text{ does not load in the factor } j.
\end{aligned}
$$

The prior variance of the difference between regimes $D_1...D_p$ is set as the prior for $A_1...A_p$.

The fourth block draws the parameters employed in the computation of the factors. Conditional on $\Sigma^{(s)}, A^{(s)}$ and $\gamma^{(s-1)}, c^{(s-1)}$, the draw $B_0^{(s)}$ is obtained using a random-walk-metropolis step as described in Carriero, Kapetanios and Marcellino (2016). This step has a tuning parameter Δ_b calibrated to achieve rejection rates of around 70%. This random-walk step employs proposal distribution variances based on factors estimated by principal component over a pre-sample period.

We also estimate a MAI specification as benchmark for the ST-MAI model and to assess the effects of nonlinearities. Carriero, Kapetanios and Marcellino (2016) use conjugate priors (normal-Wishart) for obtaining draws of A and Σ to estimate the MAI model. We use independent priors in the MAI and ST-MAI specifications, as similar priors can be also employed in the specifications with conditional heteroskedasticity. This assumption has the advantage that we are able to compare specifications using information criteria. Specifically because $var(\varepsilon_t) = \Sigma$ in the MAI model, we substitute the second block above as follows. The draw $\Sigma^{(s)}$ is from an inverse-Wishart $\Sigma^{-1} \sim W(C_1^{-1}, pv_1)$ where $C_1^{-1} = \left(\sum_{t=1}^{T} \varepsilon_t^{(s)}\varepsilon_t^{(s)\prime}\right)^{-1} + \left(0.01\mathbf{I}_{(N)}\right)^{-1}$ ($\mathbf{I}$ is an identity matrix), $pv_1 = T + pv_0$ and $pv_0 = 120$. Finally, the first block is not required.

2.3 Choosing the number of factors and the transition variable

A key component for the specification of the ST-MAI model is the choice of the number of factors, and of the factor to be used as transition variable.

To decide the number of factors for (constant parameter) MAI models, Carriero, Kapetanios and Marcellino (2016) suggest to use the marginal data density (MDD). However, the MDD of ST-MAI models is not available analytically, and limited experimentation with computational approaches was not satisfactory. However, the number of factors in a MAI model can be indicative of that in the corresponding ST-MAI model. As an alternative, the choice can be driven by economic considerations, or alternative specifications can be compared according to other criteria, such as penalized in-sample fit or forecasting capacity. In our empirical application, as the dataset is similar to that in Carriero, Kapetanios and Marcellino (2016) but with a larger number of credit indicators, we will use four factors. To the real, nominal and monetary factors of Carriero, Kapetanios and Marcellino (2016), we add a credit factor.

Assuming the number of factors is known, we need a procedure to select a transition variable from the set of factors (or other relevant variables). As mentioned, we are not able to use the marginal data density. Hence, we propose to use the Bayesian information criterion (BIC).

Assuming that θ is the vector of all the model parameters, such that $\ln f(y|\theta)$ is the log-likelihood value at a given set of parameters θ, where $y = \{Y_t\}_{t=p+1}^{t=T}$, the BIC is then

$$BIC = -2E_\theta[\ln f(y|\theta)] + \ln(T-p)[2Np + N - R], \tag{9}$$

where $E_\theta[\ln f(y|\theta)]$ is estimated by averaging the likelihood over the kept MCMC draws, and the penalty term is set for the ST-MAI specification. Because the penalty term will not vary with the choice of transition variable over alternatives $g_t^{(1)}, ..., g_t^{(R)}$, the use of BIC to choose the transition variable is equivalent to maximize the average likelihood.

2.4 Responses to common structural shocks

If we multiply equation (5) by B_0, we get:

$$F_t = B_0 \sum_{u=1}^{p} A_u F_{t-u} + B_0 \sum_{u=1}^{p} G_t(\gamma, c, x_{t-1}) D_u F_{t-u} + u_t, \tag{10}$$

with

$$u_t = B_0 \varepsilon_t, \quad var(u_t) = \Omega_t = B_0 \Sigma_t B_0'.$$

The model in (10) is a smooth transition VAR for the observable factors F_t. Hence, while the matrix B_0 that determines the composition of the factors is stable, the factor dynamics exhibit regime changes over time.

Our main interest is to measure asymmetries in the transmission of the structural shocks to the factors v_t underlying the reduced form shocks u_t. Because of the nonlinear dynamics in the model, we need to compute generalized responses (Koop, Pesaran and Potter, 1996). Specifically, we compute two responses conditional to each regime at the time of the shock, but we allow for regime changes after the shock.

The impact effect of structural shocks to the observable factors, the common shocks, are computed as in Carriero, Kapetanios and Marcellino (2016). We compute responses under the assumption that we are either in regime 1 or regime 2 at the time of the shock. It is important to emphasize, however, that later regime changes are allowed as a consequence of the shocks.

Assume first that we want to compute responses assuming that the macroeconomy is initially in regime 1. We first apply a Cholesky decomposition of the variance-covariance matrix of the factor shocks u_t to identify the R structural shocks:

$$\Omega_1 = B_0 \Sigma_1 B_0' = P_1 P_1',$$

where P_1 is a lower triangular matrix. Then, the impact of the r^{th} common structural shock at regime 1 is computed as

$$v_1^{(r)} = \Sigma_1 B_0' P_{1(r)}^{-1\prime},$$

where $P_{1(r)}^{-1\prime}$ means we use a specific column referring to common shock r of the matrix $P^{-1\prime}$ $(r = 1, ..., R)$.[2]

Similarly if we are initially in regime 2, the impact of the shock is:

$$v_2^{(r)} = \Sigma_2 B_0' P_{2(r)}^{-1\prime} \text{ where } \Omega_2 = P_2 P_2'.$$

The responses of the vector Y_t to shock $v^{(r)}$ at horizon h conditional on the history at t are:

$$GR_{h,r,t} = E[Y_{t+h}|I_t, v^{(r)}; A, B_0, \Sigma_{t+h}|I_t, \gamma, c] - E[Y_{t+h}|I_t; A, B_0, \Sigma_{t+h}|I_t, \gamma, c] \quad (11)$$

where $I_t = (Y_t', .., Y_{t-p+1}')'$ and $A = (A_1...A_p, D_1...D_p)'$. In other words, the $GR_{h,r}$ is the difference between $\hat{Y}_{t+h|v^{(r)}}$, which estimates the value of Y at $t+h$ after the shock $v^{(r)}$ hits

[2] Other identification methods are of course possible but, as we will see, the Cholesky approach can be well justified in our empirical application and it produces interesting and sensible results.

the system, and $\hat{Y}_{t+h}$, which estimates values for the same variable assuming that only usual shocks hit the system. In both cases, the average paths $\hat{Y}_{t+1|v^{(r)}}, ..., \hat{Y}_{t+h|v^{(r)}}$ and $\hat{Y}_{t+1}, ..., \hat{Y}_{t+h}$ are computed using K simulated paths for Y values obtained with usual shocks from $\varepsilon_{t+h}^{(k)} \sim N(0, \Sigma_{t+h}^{(k)})$ where $k = 1, ..., K$.[3]

The variance-covariance matrix of the usual shocks depends on the smooth transition function, that is a function of x_{t+h-1}, which in turn is a linear combination of Y_{t+h-1}. This implies that Σ_{t+h} is affected by the shock $v^{(r)}$ and may change as $h = 1, ..., H$. Hence, for each path k, Y values are simulated using:

$$
\begin{aligned}
\varepsilon_{t+h}^{(k)} &\sim N(0, \Sigma_{t+h|t}^{(k)}) \\
\Sigma_{t+h|t}^{(k)} &= (1 - \Pi_{t+h}(\gamma, c, x_{t+h-1}^{(k)}))\Sigma_1 + \Pi_t(\gamma, c, x_{t+h-1}^{(k)})\Sigma_2.
\end{aligned}
$$

An implication of equation (11) is that we have one response function over horizons $h = 1, ..., H$ to the shock $v^{(r)}$ at each point in time (I_t for $t = p+1, ..., T$). For clarity, we present responses that are averaged over a set of histories defined by the estimated regimes. This implies that we compute responses conditional on the regime at the impact. Define $I^{(reg1)}$ as the histories I_t such that $\Pi_t(\gamma, c, x_{t-1}) < 0.5$ for $t = p+1, ..., T$, and $I^{(reg2)}$ as the history values such that $\Pi_t(\gamma, c, x_{t-1}) \geq 0.5$.[4] Then the generalized responses conditional on regime 1 are:

$$
\begin{aligned}
GR_{h,r}^{reg1} &= 1/T_1 \sum_{t=1}^{T_1} GR_{h,r,t}^{(reg1)} \qquad (12) \\
GR_{h,r,t}^{(reg1)} &= E[Y_{t+h}|I_t^{(reg1)}, v_1^{(r)}; A, B_0, \Sigma_{t+h}|I_t^{(reg1)}, \gamma, c] \\
&\quad -E[Y_{t+h}|I_t^{(reg1)}; A, B_0, \Sigma_{t+h}|I_t^{(reg1)}, \gamma, c]
\end{aligned}
$$

where T_1 is the number of observations in the regime 1 history, that is, the number of times

[3] In the empirical application, we set K to 100.

[4] We could also employ different thresholds to split the sample across regimes. For example, one could define the first regime as $G_t(\gamma, c, x_{t-1}) < 0.3$, and the second regime as $G_t(\gamma, c, x_{t-1}) > 0.7$. This would remove intermediary observations to sharpen regime identification. In our empirical application, estimates of γ are large, implying almost no observations in these intermediary values, and that small changes on how we define regime-dependent histories do not affect our results.

that $\Pi_t(\gamma, c, x_{t-1}) < 0.5$ holds.[5] Similarly for regime 2:

$$
\begin{aligned}
GR^{reg2}_{h,r} &= 1/T_2 \sum_{t=1}^{T_2} GR^{(reg2)}_{h,r,t} \\
GR^{(reg2)}_{h,r,t} &= E[Y_{t+h}|I^{(reg2)}_t, v^{(r)}_2; A, B_0, \Sigma_{t+h}|I^{(reg2)}_t, \gamma, c] \\
&\quad - E[Y_{t+h}|I^{(reg2)}_t; A, B_0, \Sigma_{t+h}|I^{(reg2)}_t, \gamma, c].
\end{aligned} \tag{13}
$$

2.4.1 Algorithm to compute responses

The computation of the responses above is for a given set of parameters values $(A^{(j)}, B^{(j)}_0, \Sigma^{(j)}, \gamma^{(j)}, c^{(j)})$. We use J equally-spaced draws from the posterior distribution of the parameters to compute $GR^{reg1,(j)}_{h,r,t}$ and $GR^{reg2,(j)}_{h,r,t}$ with the aim of incorporating parameter uncertainty $(j = 1, ..., J)$. Then our estimated response to the common shock r at regime 1 is the mean of $GR^{reg1,(j)}_{h,r,t}$ for $j = 1, ..., J$, and confidence bands are computed using percentiles (16%, 68%) based on the same set of values $GR^{reg1,(j)}_{h,r,t}$. The complete algorithm for the computation of these regime-dependent responses at time of the shock is:

1. Draw a set of parameters – $A^{(j)} = (A^{(j)}_1, .., A^{(j)}_p, D^{(j)}_1, .., D^{(j)}_p), B^{(j)}_0, \Sigma^{(j)}_1, \Sigma^{(j)}_2 \gamma^{(j)}, c^{(j)}$– from saved posterior distribution draws.

2. Using the transition function $\Pi_t(\gamma^{(j)}, c^{(j)}, x^{(j)}_{t-1})$, define the set of regime 1 and regime 2 histories ($I^{(reg1)}_t$ and $I^{(reg2)}_t$).

3. Using the $A^{(j)}, B^{(j)}_0, \Sigma^{(j)}, \gamma^{(j)}, c^{(j)}$ and the set of histories from regime 1, compute a set of K paths with and without the impact of $v^{(r)}_1$ for each history $t = 1, ..., T_1$. These paths are $Y^{(k)}_{t+1|v^{(r)}_1}, ,Y^{(k)}_{t+h|v^{(r)}_1}$ and $Y^{(k)}_{t+1}, ,Y^{(k)}_{t+h}$ for $k = 1, ..., K$, where K is the number of replications to approximate the conditional means. Based on the average over the K paths, we obtain $\widehat{Y}_{t+1|v^{(r)}_1},...,\widehat{Y}_{t+h|v^{(r)}_1}$ and $\widehat{Y}_{t+1},...,\widehat{Y}_{t+h}$ for each set of histories. These paths are obtained by simulating the system using draws from $\varepsilon^{(k)}_{t+h} \sim N(0, \Sigma^{(k)}_{t+h|t})$. This implies that we simulate paths also for $\Sigma^{(k)}_{t+1|v^{(r)}_1},...,\Sigma^{(k)}_{t+h|v^{(r)}_1}$ and $\Sigma^{(k)}_{t+1},...,\Sigma^{(k)}_{t+h}$. The regime 1 responses are computed by taking the differences between the average paths (with and without the shock) for each history, and then obtaining regime 1 response as the average response over all regime 1 histories.

[5] We accumulate the responses over horizons after the computation in (12) because all variables in Y_t are in growth rates.

4. Using the $A^{(j)}, B_0^{(j)}, \Sigma^{(j)}, \gamma^{(j)}, c^{(j)}$ and the set of histories from regime 2, compute the paths as described in (3) using instead the shock $v_2^{(r)}$ for each history $t = 1, ..., T_2$. Compute then the regime 2 responses by taking the differences between the average paths (with and without the shock) for each history, and then computing the average response over all regime 1 histories.

5. Repeat 1-4 for $j = 1, ..., J$.

6. Use $GR_{h,r}^{reg1,(j)}$ and $GR_{h,r}^{reg2,(j)}$for $j = 1, .., J$ to compute the median response and 68% confidence intervals conditional on each regime and for $h = 1, ..., H$.

2.4.2 Sign Asymmetries

In addition to amplification effects depending on the regime at the time of shock, ST-MAI models are also able to deliver significant different responses to positive and negative shocks. To assess the relevance of asymmetries at a specific point in time, we compute:

$$\begin{aligned} AGR_{h,r,t} &= \{E[Y_{t+h}|I_t, v^{(r)}; A, B_0, \Sigma_{t+h}|I_t, \gamma, c] - E[Y_{t+h}|I_t; A, B_0, \Sigma_{t+h}|I_t, \gamma, c]\} - \\ &\quad \{E[Y_{t+h}|I_t, (-v^{(r)}); A, B_0, \Sigma_{t+h}|I_t, \gamma, c] - E[Y_{t+h}|I_t; A, B_0, \Sigma_{t+h}|I_t, \gamma, c]\}. \end{aligned}$$

The more asymmetric the responses, the larger $AGR_{h,r,t}$ (in absolute value). We modify the algorithm described in section 2.3.1 to compute $AGR_{h,r,t}^{(reg1)}$ in step 3 and $AGR_{h,r,t}^{(reg2)}$ in step 4. This implies we aim to compute:

$$\begin{aligned} AGR_{h,r}^{reg1} &= 1/T_1 \sum_{t=1}^{T_1} AGR_{h,r,t}^{(reg1)} \\ AGR_{h,r}^{reg2} &= 1/T_2 \sum_{t=1}^{T_2} AGR_{h,r,t}^{(reg2)}. \end{aligned}$$

As in the case of the responses, we compute 68% confidence bands for each asymmetry measure at horizons $h = 1, ..., H$. These bands are employed to assess whether asymmetries are statistically significant since if there is no sign asymmetry we expect that confidence bands will always include zero.

3 Credit Conditions and the Effects of Economic Shocks

We now want to exploit the econometric set-up we have built to address a set of empirical questions. First, do credit conditions trigger changes in the dynamic relationships among economic variables? Second, do they amplify the effects of economic shocks? Third, do they generate asymmetries in the effects of economic shocks?

We use a data set of 20 monthly (endogenous) variables for the USA, which includes the economic activity, monetary and price variables in the "medium" dataset of Bańbura et al. (2010) plus additional indicators of credit conditions, as described in Table 1. As our sample includes the zero lower bound period, we use the end-of-period effective fed fund rates for most months, except for the period where the zero lower bound is binding, where we use the Wu and Xia (2015) shadow rate as published in the Atlanta Fed website. We also use the one-year Treasury bill to help to capture the effects of unconventional monetary policy. We use six variables to measure credit conditions. The first one is the excess bond premium computed using corporate bond yields by Gilchrist and Zakrajsek (2012). This measure was employed by Lopez-Salido et al. (2017) to measure confidence in the credit market. The remaining five spread measures have been considered by Hatzius et al. (2010) and are also part of financial stress indices periodically released by regional Feds (Chicago, St. Louis and Cleveland). The set of spreads include the 3-month commercial paper spread over the 3-month Treasury bill, which was employed as transition variable by Balke (2000). It also includes the term spread measured by the difference between 10 year and 3-month Treasury rates.

The sample period is from 1974M1 up to 2016M8, but the period up to 1982M2 is employed as pre-sample to obtain mean and variances for the proposal distributions for the random walk metropolis step employed on the estimation of the factor loadings B_0. Variables are transformed as indicated in Table 1 and the MAI is estimated to their normalized values.

We set the number of factors to four. Basically, we add a credit factor to the real, nominal and monetary factors of Carriero, Kapetanios and Marcellino (2016). The monetary policy variables are not part of the credit factor so that we are able to disentangle monetary policy shocks from credit market shocks. Burnnermeier et al. (2017) argue in favour of this differentiation to understand the impact of credit on economic activity. Figure 1 shows the estimated factors using the MAI model. We label the factors as economic activity, inflation, monetary policy and credit following the variables that load on these factors in Table 1.

To provide a better understanding of these factors, we evaluate correlations between the estimated factors and alternative economic indexes. Table 2 shows correlations between the annualized factors and a set of economic and financial indexes. These include the Philadelphia Fed Coincident Economic Activity index and the Chicago Fed Financial Condition Index (including the version adjusted to remove endogenous macroeconomic effects). For the computations in Table 2, we use the factors computed at the posterior mean using the MAI model.[6]

The results in Table 2 clearly suggest that the activity factor behaves as a coincident indicator. Indeed the correlation with the Philadelphia Coincident index is of 86% at the monthly frequency. The credit factor is clearly measuring financial conditions. The factor has a 78% correlation with the Chicago Fed FCI. The monetary policy factor is correlated with the activity, credit and inflation factors, and, as consequence, it is likely to describe the current monetary policy stance. We should also note that the inflation factor (which loads on four price variables) has a positive correlation (about 50%) with the Chicago Fed FCI and our credit conditions factor.

3.1 Credit conditions as transition variable

The first empirical research question to be addressed is whether credit conditions are able to characterize nonlinearities within a ST-MAI model. Table 3 presents the average likelihood and the BIC for the MAI and four different ST-MAI model specifications. They vary by the choice of factor to act as transition variable. The statistics are computed using 16,000 kept draws for each specification based on the listed hyperparameters' values. The hyperparameters of proposal distributions are set to achieve about 30% acceptance rates, while the overall prior tightness is set to maximize the average likelihood over a small grid values.

The results in Table 3 indicate that the credit factor is the transition variable that provides the best fit for the 20 variables in the model. The second best variable to characterize regime changes is the activity factor, which is able to deliver regime changes that are highly correlated with NBER business cycle phases.

Figure 2 shows the values of the transition function using the credit factor as transition variable $[\Pi_t(\gamma, c, g_{t-1}^{(4)})]$ at the posterior mean. The dotted lines are 68% confidence bands for the transition function, and the blue line is the credit factor at the posterior mean. The Figure also includes NBER recession dates. It is clear that what we have estimated as the upper regime

[6] The model is estimated as described in section 2.2 with 20,000 draws where the first 4,000 are discarded for the computation of the posterior mean.

has anticipated both the 90-91 and the 2001 recessions. The upper regime dates also coincide with the NBER 2008-2009 recession. Following the use of credit conditions as part of financial condition indices and their use for identification of financial stress periods, we call the upper regime as the "high credit stress" regime and the lower regime as the "low credit stress" regime.

3.2 Credit conditions as shock amplifiers

Our previous results support the use of credit conditions to characterize changes in the dynamic relationships among the 20 variables listed in Table 1. Now we assess whether credit conditions can also cause the amplification of shocks. Specifically, we evaluate the responses to structural shocks of six key indicators selected from the 20 variables in Table 1.[7] We have two measures of economic activity: industrial production and unemployment; two measures of credit spreads: the Gilchrist and Zakrajsek (2012) excess bond premium (EBP) and the commercial paper spread; the PCE deflator as an example of price variable; and the fed funds rate (that is equal to the shadow rate during the ZLB period) as a monetary policy measure.

As the ST-MAI model has four factors, we can identify four common shocks. We use the Cholesky-based method described in section 2.3. Following Carriero, Kapetanios and Marcellino (2016), we label the first two shocks as demand and supply shocks. Indeed, in response to the first shock industrial production, prices and the fed fund rates move together, as in the case of a demand shock. In contrast, in response to the second shock, prices and industrial production move in opposite directions. The third shock is a monetary policy shock, and indeed industrial production and prices decline in response to this shock. The fourth shock is a credit conditions shock. The identification ordering follows Gilchrist et al. (2009), who order last the credit factor in their factor augmented VAR. This implies that the credit factor can react contemporaneously to demand, supply and monetary shocks, but it has no contemporaneous effects on them.

Figures 3 to 6 show (cumulative) responses of industrial production, unemployment, the PCE deflator, the EBP, the Fed rate and the Commercial paper (CP) spread to each one of the four shocks using the ST-MAI model with credit factor as transition variable. Responses are computed for horizons from 1 up to 48 (four years) by using 200 parameters draws from the stored posterior distribution of the parameters as described in section 2.3. Dashed lines are 68% confidence bands. Responses in red assume that the shock hits in the high stress regime (regime 2), while responses in blue assume the shock hits in the low stress regime (regime 1).

[7] Responses for all other variables are available upon request.

Impact responses ($h = 1$) may change over regimes because the variance-covariance matrix of the ST-MAI model is regime dependent.

Figure 3 shows responses for a negative demand shock (an exogenous decline of the activity factor). One can observe strong amplification effects in the high stress regime in the responses of economic activity variables and prices to demand shocks. Similar sized demand shocks have their effects amplified twofold after two years if they hit in the regime of bad credit conditions. The effect of the demand shock on unemployment is an increase of about 1 percentage point after two years in times of low credit stress, but in times of high stress, this effect is 2 percentage points. An amplification of similar magnitude is also detected in the excess bond premium responses.

Similar amplification effects are also found in the responses of economic activity variables to supply shocks (Figure 4), except for the PCE deflator. Amplification effects are smaller for monetary and credit shocks (Figures 5 and 6), though still present. The response of the PCE deflator to credit is clearly amplified in the high stress regime (Figure 6). Similar results are found by Galvao and Owyang (2016): financial stress shocks have strong negative effects on prices during the high stress regime.

Interestingly, results in the response to monetary policy shocks (Figure 5) suggest that the excess bond premium increases following monetary policy tightening in the high stress regime. However, a shock of similar size has a negative effective effect on excess bond premium in the low stress regime.

These empirical results confirm the usefulness of ST-MAI models in uncovering amplification effects in the responses to structural shocks. This is achieved by allowing the parameters of the conditional mean and conditional variance to change over regimes driven by an observed set of credit spread variables. The results, obtained with a large model and with a set of credit spread measures, confirm the evidence of nonlinearity in Balke (2000), based on a small threshold VAR model with the commercial paper spread as transition variable.

3.3 Credit conditions and asymmetric shock effects

Our last empirical research question is to check whether positive and negative shocks have asymmetric effects. Figures 3 to 6 show responses from common shocks that normally have negative effects on economic activity, that is, a negative demand shock, a positive (higher prices) supply shock, a positive (tightening) monetary policy shock and a positive (wider spreads) credit shock. We now evaluate whether or not a shock of the same size but opposite sign has symmetric effects on the endogenous variables. This requires to compute the AGR asymmetry measure, as described in section 2.3.

We compute the sign asymmetry measure for responses of all the 20 variables in the VAR to each one of the four common shocks. We use 68% confidence bands to assess whether there are statistically significant asymmetries to large (two standard deviation) shocks.[8] For responses computed for shocks that hit the model in the low stress regime, we find no evidence of significant asymmetry. However, when looking at responses to shocks that hit in the high stress regime, we detect some cases of asymmetries when responses are computed to supply, monetary and credit shocks. Asymmetries are mainly detected in the responses of unemployment and of the commercial paper spread. Examples of asymmetries over the horizons from 1 to 24 months are presented in Figure 7.

Figure 7A presents sign asymmetries during the high stress regime in responses to a supply shock, while Figure 7B to a credit shock, and Figure 7C to a monetary policy shock. All asymmetry values are negative. As positive shocks lead to positive responses in the variables presented (unemployment and commercial paper spread), then significant negative values of AGR imply that negative shocks –a decrease in prices, loosing of monetary policy stance, narrowing of credit spreads– have a larger effect on these variables than positive ones. The largest negative effects are detected for the responses to supply shocks, so in Figure 7D we present, as an example, unemployment and commercial paper spread responses to positive (blue) and negative (red) shocks in the high stress regime. It is clear that these responses are not symmetric and that a shock that deflates prices reduces unemployment by 3 percentage points after two years, while a positive shock of the same size increases unemployment by a bit more than 1 percentage point after two years.

These asymmetries in the response of unemployment to shocks suggest that unemployment can strongly decrease after two years if good shocks hit the economy at the time of credit stress. This nonlinear propagation effect of credit conditions on unemployment is, as far as we are aware, novel in the empirical literature. This shows again the usefulness of a large time-varying VAR model when assessing the links between credit conditions and the macroeconomy.

[8] This is obtained by multiplying $v_1^{(r)}$ and $v_2^{(r)}$ computed as described in section X by 2. Effectively we are comparing responses to $2v_1^{(r)}$ with responses to $-2v_1^{(r)}$, and responses to $2v_2^{(r)}$ with responses to $-2v_2^{(r)}$.

4 Conclusions

This paper sheds additional light on the relationship between credit conditions and the macroeconomy. We show that credit stress, as measured by widening spreads, can alter the dynamic relationships among economic variables. Moreover, during credit stress periods, the effects of economic shocks can be amplified, and there can be sign asymmetries, so that positive and negative shocks of the same size can have different effects (in absolute value).

These empirical features emerge from a novel econometric model, a large smooth transition multivariate autoregressive index (ST-MAI) model. In the ST-MAI model all variables are driven by a small number of observable factors, and their lags. In our case, we have economic activity, prices, monetary and credit factors. The credit factor is also the preferred transition variable, the trigger of parameter changes, with a reasonable timing for the endogenously identified credit stress periods.

We develop a (Bayesian) estimation procedure for the ST-MAI model, and show how it can be used to compute (generalized) impulse response functions and measures of asymmetry.

We believe that, besides our specific application, the ST-MAI model can be an useful tool for empirical macroeconomics, as it permits to model large set of variables, taking into account parameter time variation. It is similar to a factor augmented vector autoregressive (FAVAR) model, but the observable factors simplify estimation, shock identification, and interpretation of the results.

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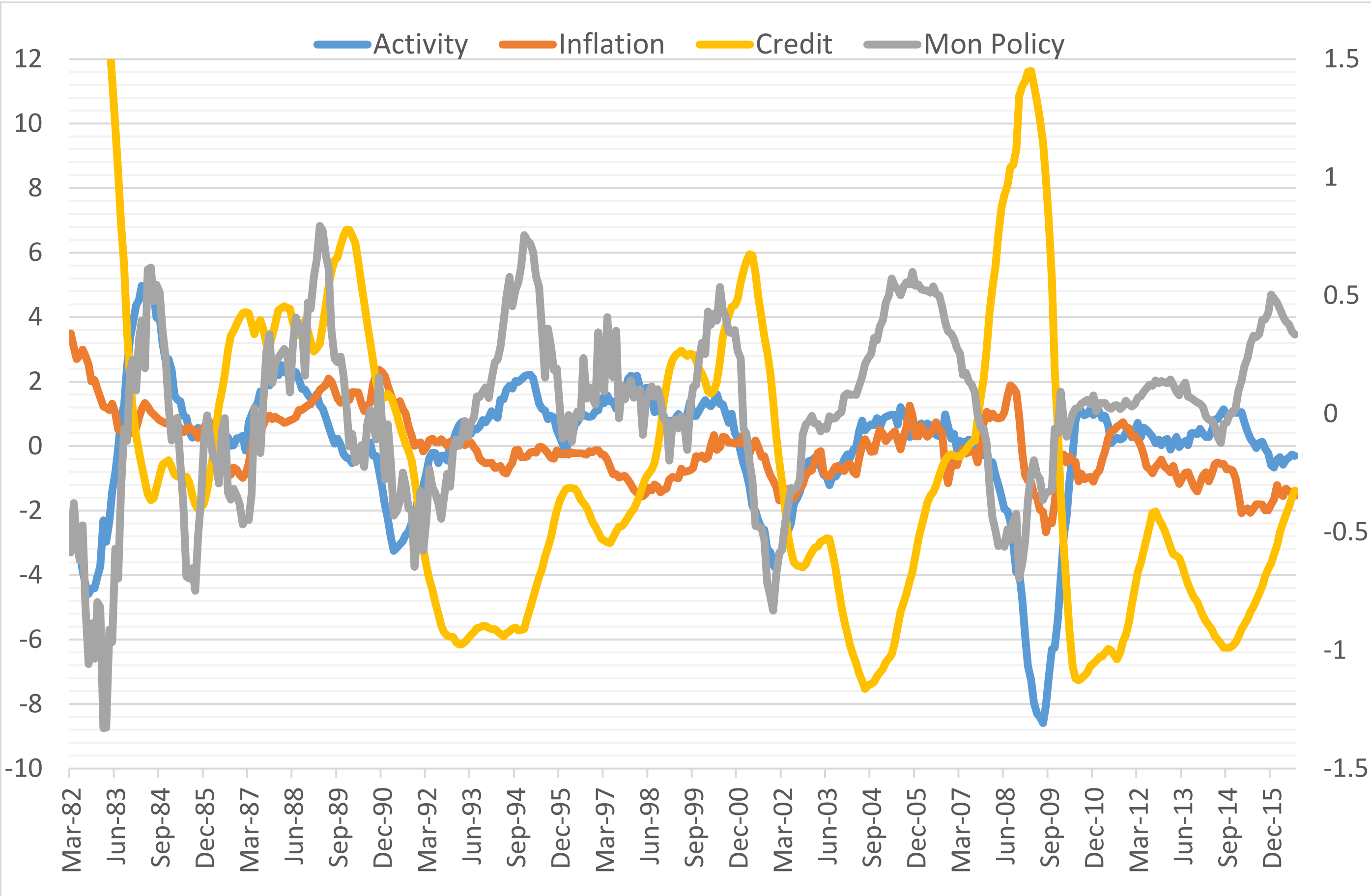
Table 1: List of endogenous variables in the (ST) MAI specifications.

	Factor	Trans.
Employees nonfarm	activity	Log-diff
Avg hourly earnings	activity	Log-diff
Personal income	activity	Log-diff
Consumption	activity	Log-diff
Industrial Production	activity	Log-diff
Capacity utilization	activity	Log-diff
Unemp. Rate	activity	Log-diff
Housing Starts	activity	Log-diff
CPI	inflation	Log-diff
PPI	inflation	Log-diff
PCE deflator	inflation	Log-diff
PPI ex food and energy	inflation	Log-diff
FedFunds + shadow rate	Mon. Pol.	diff
1year_rate	Mon. Pol.	diff
EBP	Credit	levels
BAA spread	Credit	levels
Mortgage Spread	Credit	levels
TED Spread	Credit	levels
CommPaper Spread	Credit	levels
Term Spread (10y-3mo)	Credit	levels

Note: sample period 1974M1-2016M8. Data between 1974M1 and 1982M2 is employed as pre-sample.

Figure 1: Factors estimated by MAI in annual differences.



Note: Monetary policy factor in the right axis.

Table 2: Correlations among and with MAI estimated factors

	F_infl	F_mp	F_cred	PhilFed Activity	Chicago Fed Fin Cond.	Adj. Chicago Fed Fin Cond.
F_activity	0.06	0.61	-0.47	**0.86**	-0.39	-0.02
F_inflation	1	-0.13	0.48	-0.11	0.54	0.12
F_mp	-0.13	1	-0.49	0.63	-0.34	-0.07
F_credit	0.48	-0.49	1	-0.51	**0.78**	**0.53**

Table 3: Measures of fit for different ST-MAI specifications

	Average Likelihood	BIC
F_activity as trans. var. (λ_1=1;Δ_Σ=25/110; $\Delta_{\gamma,c}$=0.01)	-7820.760	28271.735
F_inflation as trans. var. (λ_1=1;Δ_Σ=120/20; $\Delta_{\gamma,c}$=0.01)	-8004.157	28638.529
F_mp as trans. var. (λ_1=1;Δ_Σ=20/120; $\Delta_{\gamma,c}$=0.01)	-7859.639	28349.943
F_credit as trans. var. (λ_1=1;Δ_Σ=120/20; $\Delta_{\gamma,c}$=0.01)	-7749.376	28128.967

Note: All specifications with 4 factors set as in Table 1. Hyperparameters are chosen to maximise the average likelihood and/or set acceptance rates to about 30%.

Figure 2: Regime changes in ST-MAI model with F_credit as Regime-Switching Variable.

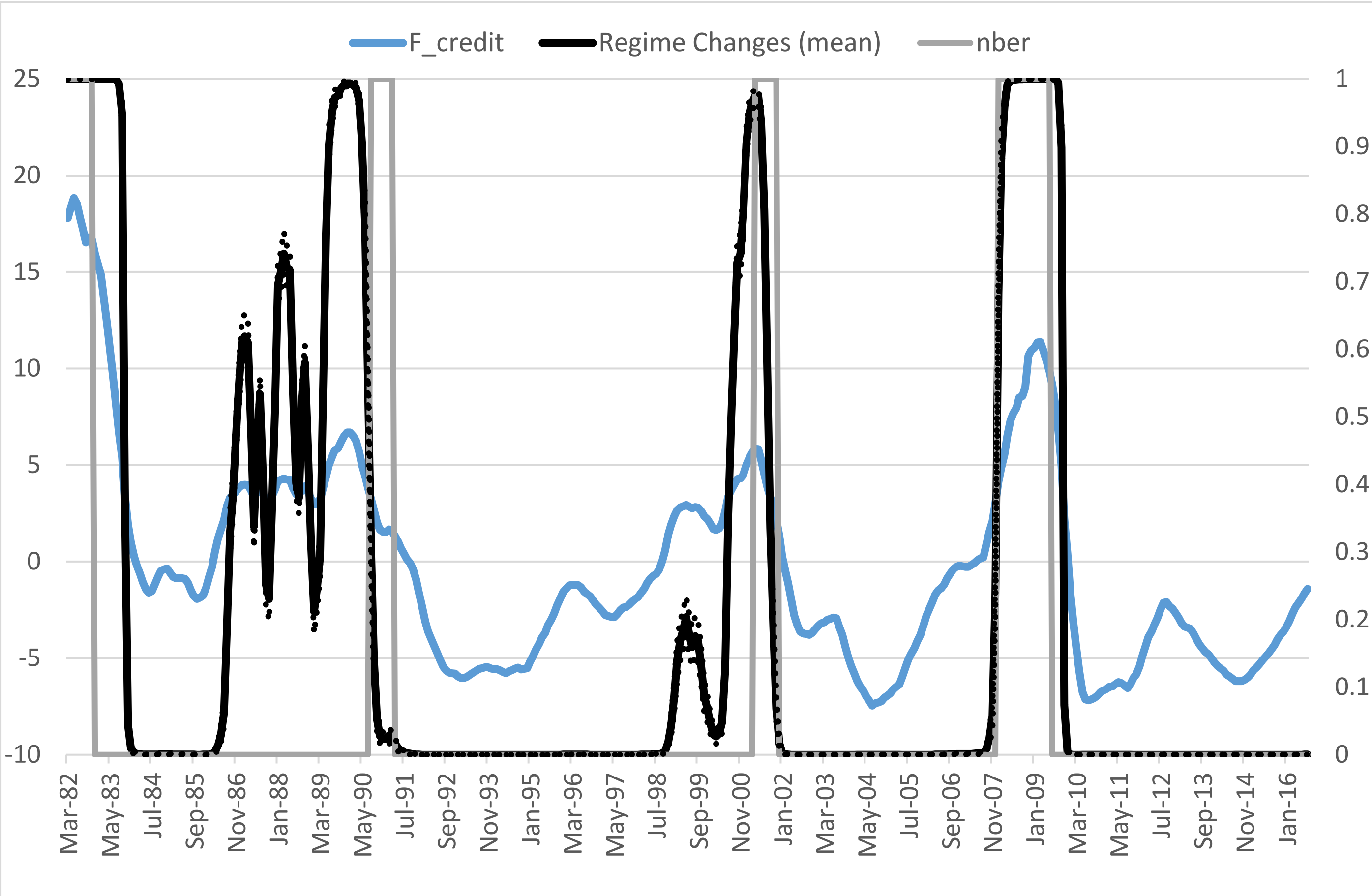
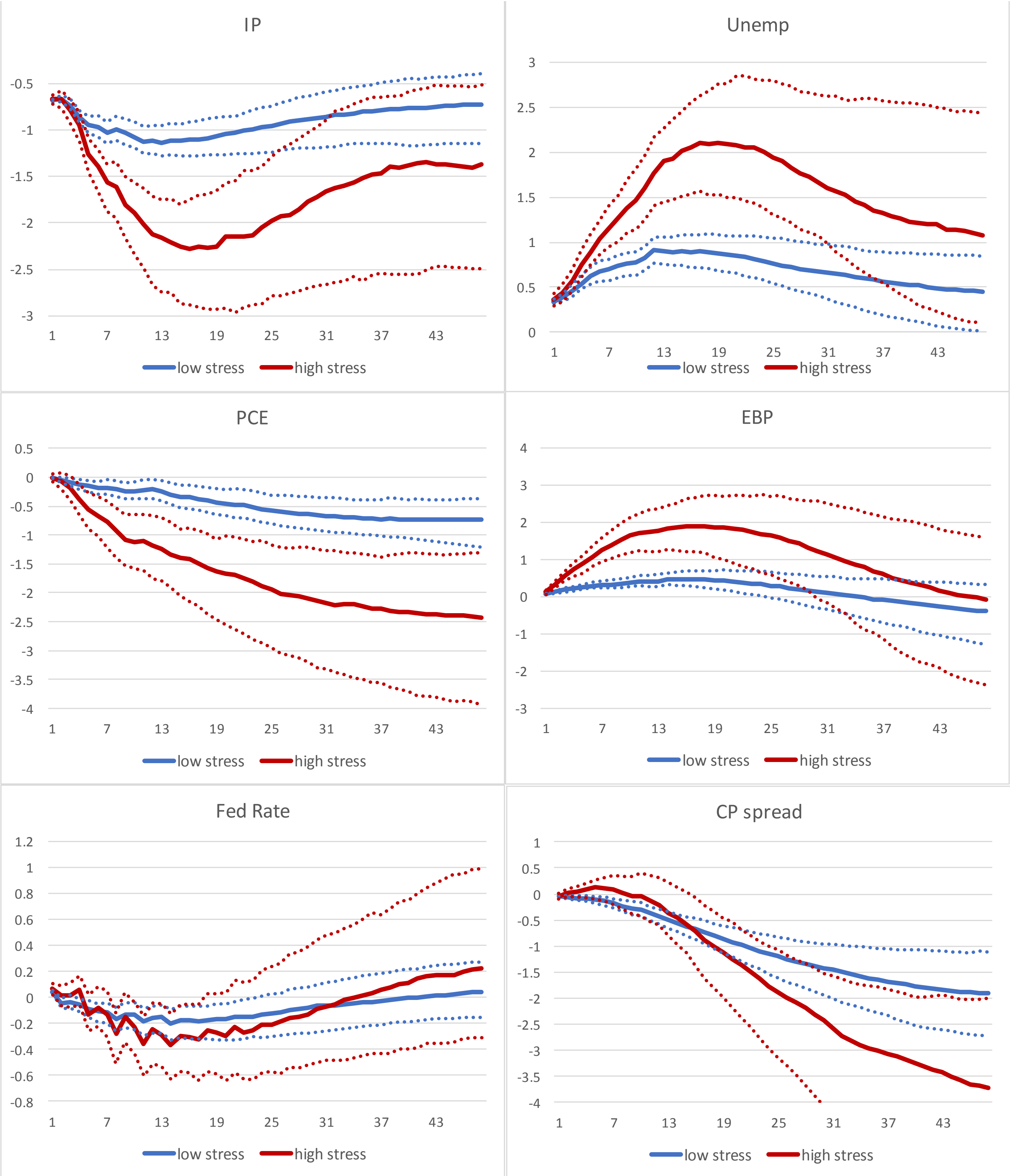
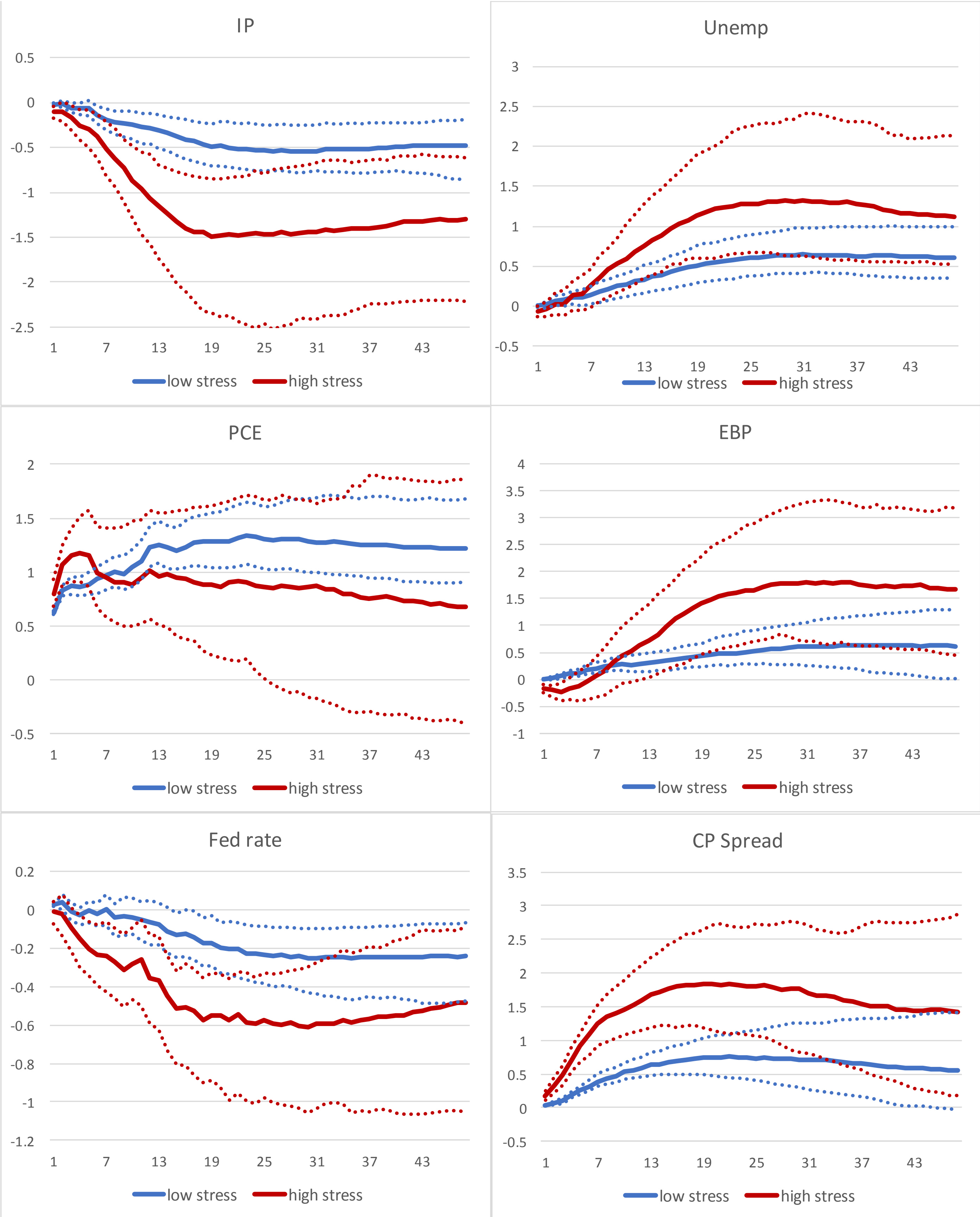


Figure 3: ST-MAI model responses to demand shock



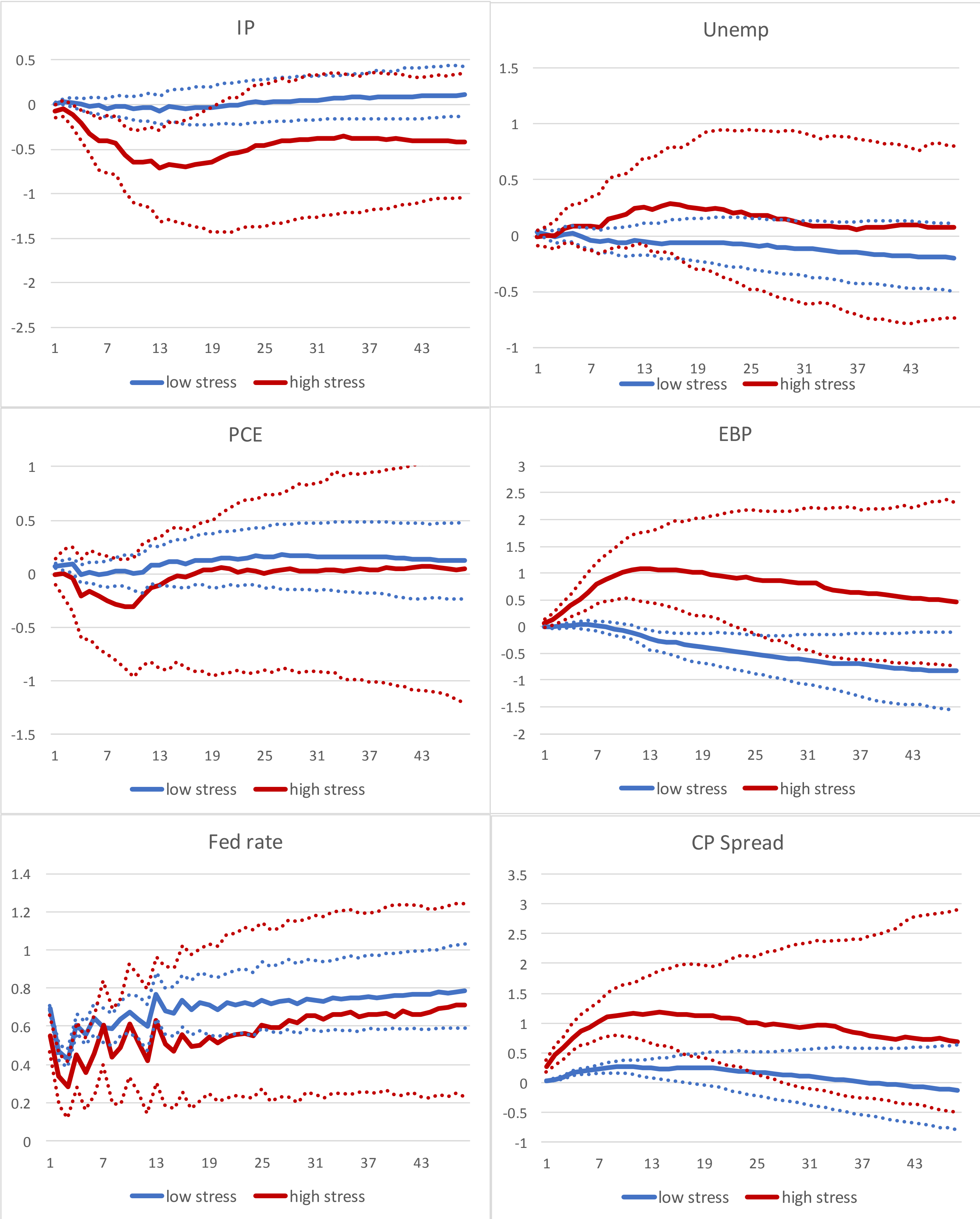
Note: Dotted lines are 68% confidence bands.

Figure 4: ST-MAI model responses to supply shock



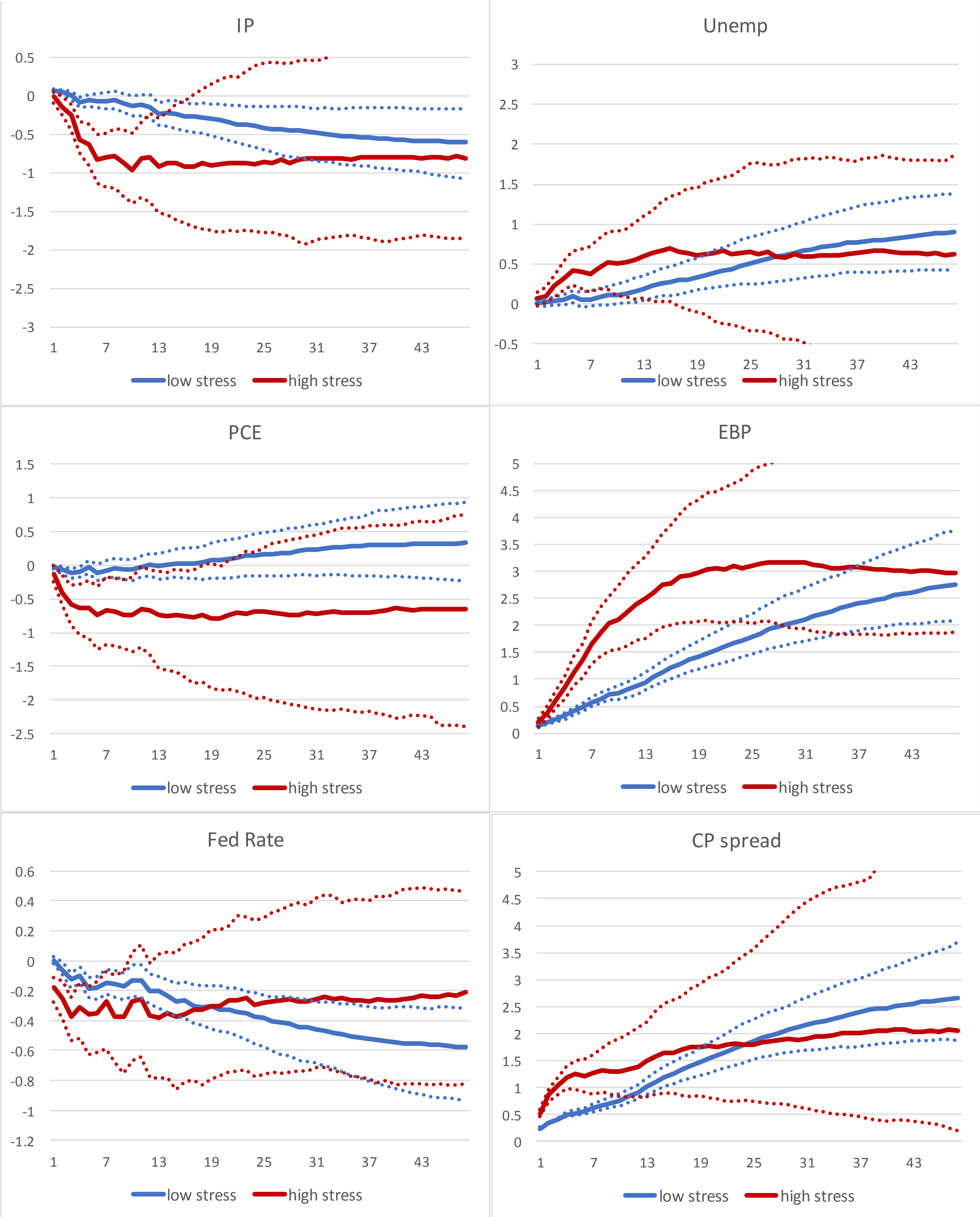
Note: Dotted lines are 68% confidence bands.

Figure 5: ST-MAI model responses to monetary policy shock



Note: Dotted lines are 68% confidence bands.

Figure 6: ST-MAI model responses to credit shocks



Note: Dotted lines are 68% confidence bands.

Figure 7: Sign Asymmetry computed with ST-MAI model

Figure 7A: Asymmetry in responses to a supply shock in the high stress regime.

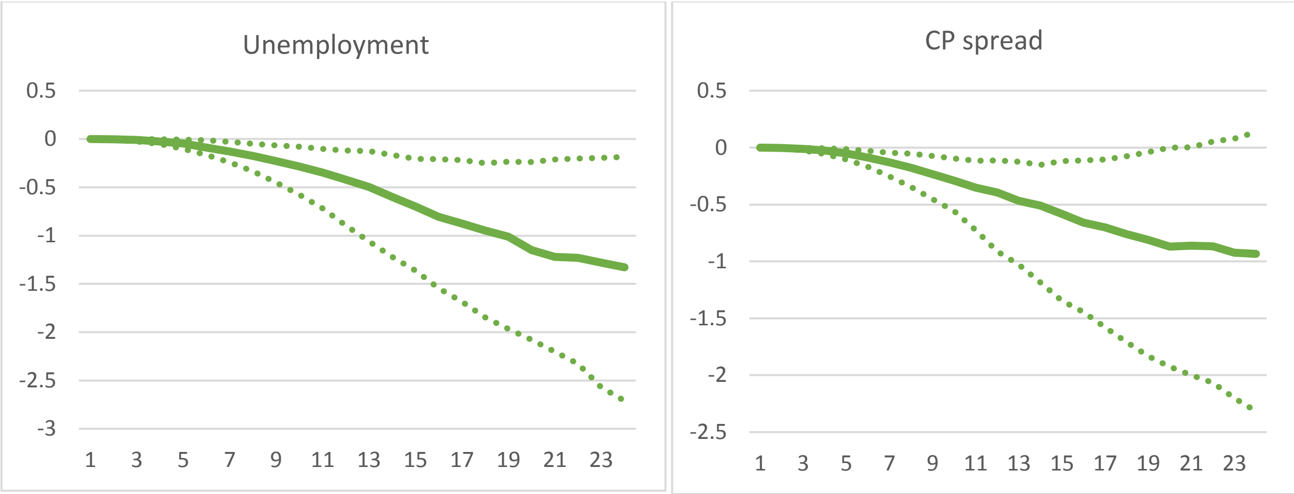


Figure 7B: Asymmetry in responses to a credit shock in the high stress regime.

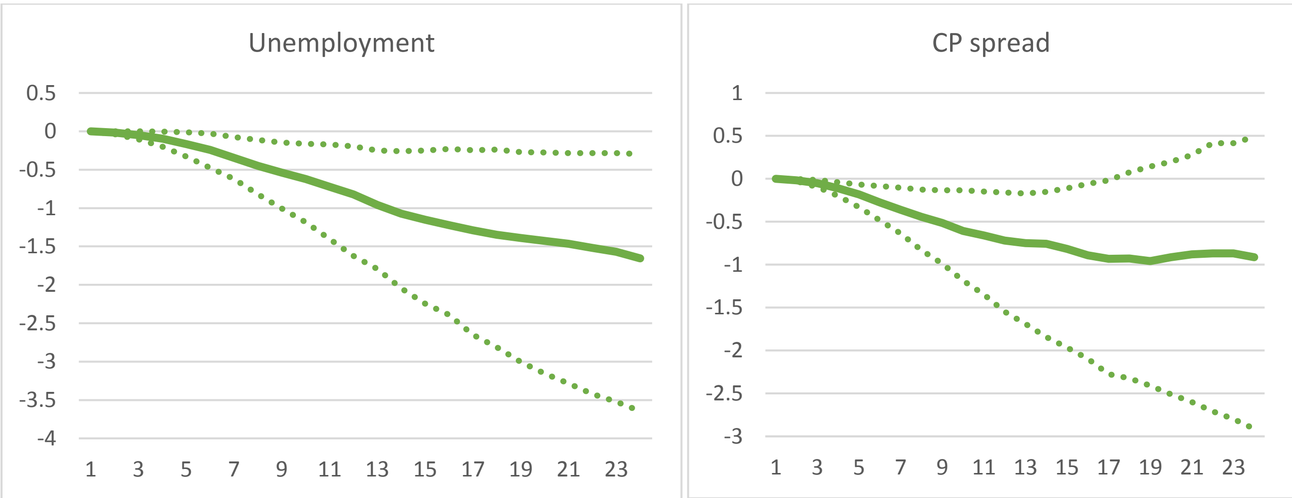


Figure 7C: Asymmetry in responses to a monetary shock in the high stress regime

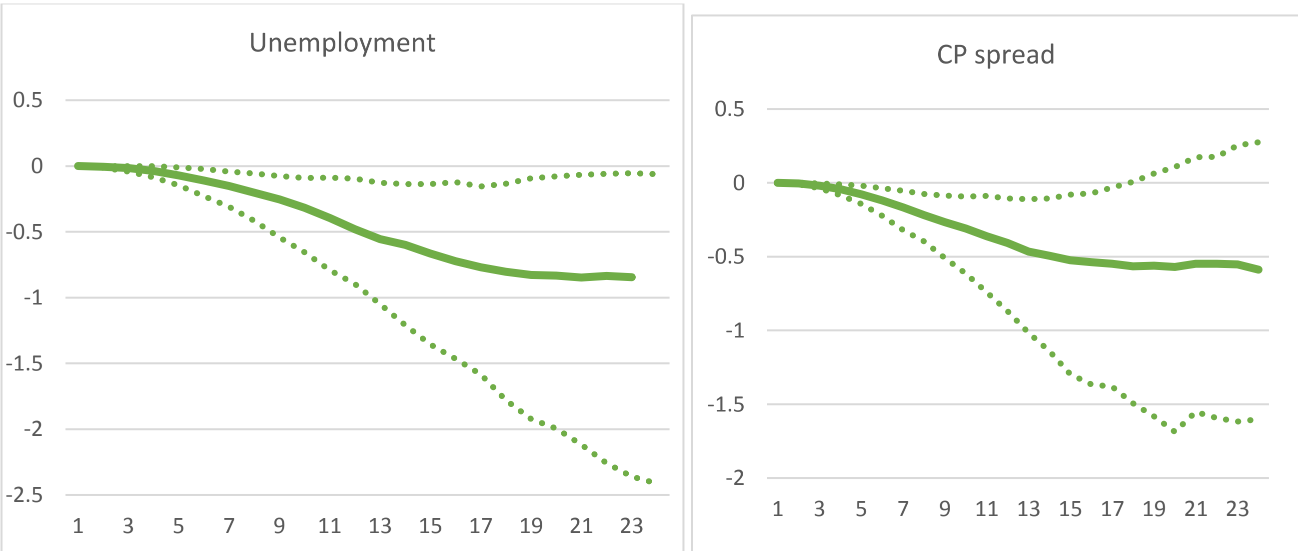


Figure 7D: Responses to a supply shock in the high stress regime