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

Andrea Carriero  Ana Beatriz Galvao
Queen Mary University of London  University of Warwick
Massimiliano Marcellino
Bocconi University and CEPR
February, 2018

Abstract

In this paper we address three empirical questions related to credit conditions. Do they change the dynamic interactions of economic variables by characterizing different regimes? Do they amplify the effects of economic shocks? Do they generate asymmetries in the effects of economic shocks depending on the size and sign of the shock? 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

*We would like to acknowledge comments and suggestions made by seminar and workshop participants at Barcelona Time Series Summer Institute, EACBN-CEPR Conference on Time-varying Models, St Louis Fed Applied Econometrics Workshop, Texas A&M, Erasmus Rotterdam, Tinbergen Institute, the EC2 Time-varying conference and the Norges Bank workshop on Nonlinear Models. Corresponding author: Dr. Ana Beatriz Galvao, EMF Group Warwick Business School, University of Warwick, Coventry CV4 7AL, United Kingdom, ana.galvao@wbs.ac.uk.
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; He and Krishnamurthy, 2013). Krishnamurthy and Muir (2017) argue that theoretical models describe financial crises, which lead to deep recessions, as the result of a negative sizeable financial shock affecting a fragile financial sector that leads to amplification of the initial shock. The implication for empirical analysis, as also suggested by Barnichon, Matthes and Ziegenbein (2017), is that shocks may have different effects depending on their size (large vs small), sign (positive vs negative) and the conditions on the financial sector.

Our paper contributes to this empirical literature. Specifically, we address three questions related to credit conditions. First, do they change the dynamic interactions of economic variables by characterizing different regimes? Second, do they amplify the effects of economic shocks? Third, do they generate asymmetries in the effects of economic shocks depending on the size and sign of the shock?

From an econometric point of view, to answer these questions we develop a particular Smooth Transition Vector Autoregressive (ST-VAR) model, which is simple, intuitive and computationally feasible.

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, 2017). 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. In comparison with the nonlinear projection approach in Barnichon et al. (2017) that uses the sign of past structural shocks to describe changes in the shock transmission, ST-VAR models employ a set of observed endogenous variables to
characterize regime changes, implying that the regime may change endogenously as response to shocks.\footnote{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, 2017).}

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 (Báˇn´bara, Giannone and Reichlin, 2010; Giannone, Lenza and Primiceri, 2015; Brunnermeier, 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 (2017) employ factor augmented VAR models to deal with this dimensionality issue.

In this paper we propose an approach that allows for the estimation of ST-VAR models with a large number of endogenous variables. We do so by casting the ST-VAR in the Multivariate Autoregressive Index (MAI) representation of Reinsel (1983) and Carriero, Kapetanios and Marcellino (2016).\footnote{MAI models impose reduced-rank restrictions on the matrices of a VAR model which imply that each variable is driven by (the lags of) a limited set of linear combinations of all variables, interpreted as observable factors (indices). In this sense, MAI models are a bridge between VAR and factor-augmented VAR models with the advantage that the factors can be consistently estimated even if the number of variables is finite.} The approach has several advantages for 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 regime changes. We introduce smooth transition regime changes 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 regime changes.

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 (2017) 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 (2017). We use the method proposed by Carriero, Kapetanios and Marcellino (2016) to estimate factors’ loadings. Because the variance-covariance matrix changes with the
regime, we use the triangularization method proposed by Carriero, Clark and Marcellino (2016) to further reduce the computational time caused by the large number of endogenous variables.

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 a specification based on four factors: a real factor, a nominal factor, a monetary factor, and credit factor. 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)). We find overwhelming evidence (based on the Bayesian Information Criterion) that the credit factor is the main trigger of regime changes. This answers our first research question, showing strong evidence that credit conditions change the dynamic interactions of economic variables.

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 and to large and small shocks when the model is in the credit stress regime. Shocks that decrease either the policy rate, prices or credit spreads have faster and stronger effects on unemployment than shocks that increase these variables. And, if these shocks are large, they have disproportionate larger effects on unemployment and the policy rate if they hit the economy in a period of credit stress. Hence, to answer our third question, we also find evidence that credit conditions can trigger asymmetric effects of economic shocks. Shocks can have asymmetric effects in the ST-MAI model because they can change the probability of regime changes, as the variables that underlie changes are endogenous in the model.

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 three empirical research questions. It also presents results from a small ST-VAR model to show the relevance of using a larger information set for structural analysis in order to alleviate omitted variable problems. 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 depending on credit conditions. 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($p$):

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

with $\varepsilon_t \sim i.i.d. N(0, \Sigma)$, $t = 1, ..., T$, and we omit deterministic terms just for notational convenience. The number of the VAR($p$) parameters grows proportionally to $N^2$ when $p$ increases, 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) can be written as:

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

or

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

where

$$F_t = B_0 Y_t.$$
The $R$ variables in $F_t$ can be considered as observable factors (indices), driving the dynamics of all the variables. Of course, some restrictions need to be put on $B_0$ to ensure identification. 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 $N^2p$ 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.

Carriero, Kapetanios and Marcellino (2016) show how to estimate the parameters of the MAI model using an MCMC algorithm, and how to select the number of factors. MAI models are a special case of general reduced-rank VARs with the advantage that they imply a VAR instead of a VARMA model for the observed factors, which is convenient for structural analysis.

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

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

where $\Pi_t(\gamma, c, x_{t-1})$ is a logistic function, $x_t$ is the transition variable, $c$ is the threshold, and $\gamma$ 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 much lower than the threshold, $\Pi_t(\gamma, c, x_{t-1})$ gets close to 0, and the coefficients are $A_u$. This means that $D_u$ measures the difference in conditional mean dynamics between regimes. When the smoothing parameter $\gamma$ 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 the key drivers of fluctuations in the variables in $Y_t$. Hence, we have:

$$\Pi_t(\gamma, c, x_{t-1}) = \frac{1}{1 + \exp\left(-\left(\frac{\gamma}{\sigma_x}(x_{t-1} - c)\right)\right)},$$

where $x_t = f_t^{(r)}$, that is, the transition variable is one of the $R$ observable factors in $F_t$ (with

\begin{footnote}{For surveys on smooth transition VARs, see Van Dijk, Terasvirta and Franses (2002) and Hubrich and Terasvirta (2013).}

\end{footnote}
standard deviation $\sigma_x$):

$$f^{(r)}_t = b_0^{(r)} Y_t,$$

and $b_0^{(r)}$ the $r^{th}$ $(1 \times N)$ row of the matrix $B_0, r = 1,..,R$. 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.\footnote{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.}

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:

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

(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 the error variance of the $N \times 1$ vector of reduced-form disturbances $\varepsilon_t$ as follows:

$$\text{Var}(\varepsilon_t) = \Sigma_t = (1 - \Pi_t(\gamma, c, x_{t-1}))\Sigma_1 + \Pi_t(\gamma, c, x_{t-1})\Sigma_2,$$

(8)

where $\Pi_t(\gamma, c, x_{t-1})$ is the 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 $\Sigma_1$, but if the value of $\Pi_t(\gamma, c, x_{t-1})$ is approximately 1, then the variance-covariance matrix is at $\Sigma_2$. As before, the transition variable $x_t$ is the year-on-year growth equivalent of one of the factors, $g_t^{(r)}$. 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).

When estimating large VAR models with changes in the variance-covariance matrix Carriero, Clark and Marcellino (2016) allow the variances to change over time (diagonal of $\Sigma_t$), while covariances (elements outside the diagonal) are fixed. Our regime-dependent smooth transition specification is a parsimonious method to also allow for covariance changes over regimes. 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:

\[ Z_t = (F_{t-1}^0, \ldots, F_{t-p}^0, \Pi_t(\cdot)F_{t-1}^0, \ldots, \Pi_t(\cdot)F_{t-p}^0)^\prime, \]

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

\[ A = (A_1 \ldots A_p, D_1 \ldots D_p)^\prime, \]

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

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

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

The proposed algorithm includes three Metropolis steps in a Gibbs sampling approach. The algorithm has four blocks to obtain \( S \) conditional draws for all parameters.

The first block draws the parameters of the transition function similarly to Galvao and Owyang (2017). 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, for \( s = 1, \ldots, S \). This assumes a gamma prior distribution for \( \gamma \), and a normal distribution for \( c \). The proposal distribution for \( \gamma \) 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 \( \Delta_\gamma^2 \). 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 \( f_t^{(r)} \) or its yearly growth rate \( g_t^{(r)} \). Both tuning parameters \( \Delta_\gamma \) and \( \Delta_\gamma \) are set to achieve rejection rates of around 70%. In the empirical application, the prior for \( \gamma \) 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 an inverse-Wishart proposal distribution as in Galvao and Owyang (2017). The priors for the variance-covariance matrix of the first regime is set as \( \Sigma_0^{(s)} \sim W(C_0^{-1}, pv_0) \) where \( C_0 = T\Sigma \) and \( \Sigma \) is a diagonal
the proposal distribution is $\var{\Sigma}^{-1} \sim W(C_1^{-1}, pv_1)$ with $pv_1 = pv_0 + \Delta_1 \sum_{t=1}^{T} I(f_{t}^{(i)} \leq c)$ [I(.) is an indicator function] and $C_1 = \Delta_1 \sum_{t=1}^{T} \epsilon_{1t}e_{1t}^{(')}$ where $e_{1t} = [1 - \Pi_t (\gamma^{(s-1)}, c^{(s-1)}, x^{(i,s-1)}_t)]\varepsilon^{(s-1)}_t$ and $\varepsilon^{(s-1)}_t = (Y_t - Z^{(s-1)}_t A^{(s-1)})$. In the case of the variance-covariance of the second regime, we use the same prior as for the first regime, and the likelihood, the prior, and the proposal weights. This is applied separately for each 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 $\var{\Sigma}^{(s)}_1$ and $\var{\Sigma}^{(s)}_2$, that is, $\var{\Sigma}^{(s)}_1$ is obtained conditional on $\var{\Sigma}^{(s-1)}_2$, and then $\var{\Sigma}^{(s)}_2$ is obtained conditional on $\var{\Sigma}^{(s)}_1$. The two tuning parameters $\Delta_{\Sigma_1}$ and $\Delta_{\Sigma_2}$ 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 $\var{\Sigma}^{(s)}_1$, $\var{\Sigma}^{(s)}_2$, $\gamma^{(s)}$, $c^{(s)}$ and $B^{(s-1)}_0$, 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:

$$\text{var}(A^{ij}_{(l)}) = \frac{\lambda^2}{\lambda_3} \sigma^2_t$$ if the variable $i$ loads in the factor $j$ (for $l = 1, \ldots p$)

$$\text{var}(A^{ij}_{(l)}) = \frac{\lambda^2 \lambda_2}{\lambda_3} \sigma^2_t$$ if the variable $i$ does not load in the factor $j$.

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

The fourth block draws the parameters employed in the computation of the factors. Conditional on $\var{\Sigma}^{(s)}$, $A^{(s)}$ and $\gamma^{(s-1)}$, $c^{(s-1)}$, the draw $B^{(s)}_0$ is obtained using a random walk Metropolis step as described in Carriero, Kapetanios and Marcellino (2016). This step has a tuning parameter $\Delta_{\delta}$ 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. Carriero, Kapetanios and Marcellino (2016) use conjugate priors (normal-Wishart) for obtaining draws of $A$ and $\Sigma$ to estimate the MAI model. In this paper, we use independent priors to estimate the MAI model. This assumption has the advantage that it is easier compare the MAI model with
ST-MAI models, which are estimated with independent priors as described above. Specifically, because $\text{var}(\varepsilon_t) = \Sigma$ 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 $C^{-1}_1 = \left( \sum_{t=1}^{T} \varepsilon_t^{(s)} \varepsilon_t^{(s)\prime} \right)^{-1} + (0.01 \times I_N)^{-1}$ (where $I_N$ is an identity matrix of order $N$), $pv_1 = T + pv_0$ and $pv_0 = 120$. Finally, the first block is not required.

### 2.3 Responses to common structural shocks

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

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

(9)

with

$$u_t = B_0 \xi_t, \quad \text{var}(u_t) = \Omega_t = B_0 \Sigma_t B_0'$$

The model in (9) 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. Indeed, in section 3.3, we measure the probability of regime changes to evaluate asymmetries arising from the size and the sign of shocks.

Assume first that we want to compute responses when the economy 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

\[
v_1^{(r)} = \Sigma_1 B_0' P_1^{-1(r)},
\]

where \( P_1^{-1(r)} \) means we use a specific column referring to common shock \( r \) of the matrix \( P^{-1} \) \( (r = 1, \ldots, R) \), as shown in Carriero, Kapetanios and Marcellino (2016). \(^5\)

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

\[
v_2^{(r)} = \Sigma_2 B_0' P_2^{-1(r)} \text{ where } \Omega_2 = P_2 P_2'.
\]

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

\[
GR_{h,r,t} = E[Y_{t+h}|I_t, v^{(r)}; A, B_0, \Sigma_{t+h}|I_t, \gamma, c] - E[Y_{t+h}|I_t; A, B_0, \Sigma_{t+h}|I_t, \gamma, c] \quad (10)
\]

where \( I_t = (Y_t', \ldots, Y_{t-p+1}')' \) and \( A = (A_1 \ldots A_p, D_1 \ldots D_p)' \). In other words, the responses to \( v^{(r)} \) at a given point in time are computed as the difference between \( \hat{Y}_{t+h|v^{(r)}} \), which estimates the value of \( Y \) at \( t+h \) after the shock \( v^{(r)} \) hits 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 \( \hat{Y}_{t+1|v^{(r)}}, \ldots, \hat{Y}_{t+h|v^{(r)}} \) and \( \hat{Y}_{t+1}, \ldots, \hat{Y}_{t+h} \) are computed using \( K \) simulated paths for \( Y \) values obtained with usual shocks from \( \varepsilon_{t+h}^{(k)} \sim N(0, \Sigma_{t+h}) \) where \( k = 1, \ldots, K \). \(^6\)

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

\[
\varepsilon_{t+h}^{(k)} \sim N(0, \Sigma_{t+h}^{(k)})
\]

\[
\Sigma_{t+h}^{(k)} = (1 - \Pi_{t+h}(\gamma, c, x_{t+h-1}^{(k)})) \Sigma_1 + \Pi_{t}(\gamma, c, x_{t+h-1}^{(k)}) \Sigma_2.
\]

\(^5\)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.

\(^6\)In the empirical application, we set \( K \) to 100.
An implication of equation (10) is that we have one response function over horizons \( h = 1, \ldots, H \) to the shock \( v(r) \) at each point in time \( (I_t \text{ for } t = p + 1, \ldots, T) \). 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 \( I^{(\text{reg}1)}_t \) as the histories \( I_t \) such that \( \Pi_t(\gamma, c, x_{t-1}) < 0.5 \) for \( t = p + 1, \ldots, T \), and \( I^{(\text{reg}2)}_t \) as the history values such that \( \Pi_t(\gamma, c, x_{t-1}) > 0.5 \). Then the generalized responses conditional on regime 1 are:

\[
GR^{\text{reg}1}_{h,r} = \frac{1}{T_1} \sum_{t=1}^{T_1} GR^{(\text{reg}1)}_{h,r,t} \\
GR^{(\text{reg}1)}_{h,r,t} = E[Y_{t+h} | I^{(\text{reg}1)}_t, v^{(r)}_t; \gamma, \Sigma_t, c] - E[Y_{t+h} | I^{(\text{reg}1)}_t; \gamma, \Sigma_t, c]
\]

where \( T_1 \) is the number of observations in the regime 1 history, that is, the number of times that \( \Pi_t(\gamma, c, x_{t-1}) < 0.5 \) holds.\(^7\) Similarly for regime 2:

\[
GR^{\text{reg}2}_{h,r} = \frac{1}{T_2} \sum_{t=1}^{T_2} GR^{(\text{reg}2)}_{h,r,t} \\
GR^{(\text{reg}2)}_{h,r,t} = E[Y_{t+h} | I^{(\text{reg}2)}_t, v^{(r)}_t; \gamma, \Sigma_t, c] - E[Y_{t+h} | I^{(\text{reg}2)}_t; \gamma, \Sigma_t, c]
\]

The computation of the responses above is for a given set of parameters values \( (A^{(j)}, B^{(j)}, \Sigma^{(j)}, \psi^{(j)}, c^{(j)}) \). We use \( J \) equally-spaced draws from the posterior distribution of the parameters to compute \( GR^{\text{reg}1,(j)}_{h,r,t} \) and \( GR^{\text{reg}2,(j)}_{h,r,t} \) with the aim of incorporating parameter uncertainty \( (j = 1, \ldots, J) \). Then our estimated response to the common shock \( r \) at regime 1 is the mean of \( GR^{\text{reg}1,(j)}_{h,r,t} \) for \( j = 1, \ldots, J \), and confidence bands are computed using percentiles (16%, 68%) based on the same set of values \( GR^{\text{reg}1,(j)}_{h,r,t} \). The complete algorithm for the computation of these regime-dependent responses at time of the shock is described in Appendix A.

\(^7\)We could also employ different thresholds to split the sample across regimes. In the empirical application, the lower regime histories are selected such that \( \Pi_t(\gamma, c, x_{t-1}) < 0.45 \), and the upper regime histories satisfy \( \Pi_t(\gamma, c, x_{t-1}) > 0.55 \). This removes only a small number of histories and sharpens regime identification.

\(^8\)We accumulate the responses over horizons after the computation in (11) because all variables in \( Y_t \) are in growth rates.
2.3.1 Sign and Size 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. First, to simplify the notation, write:

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

Hence, asymmetries from the sign of the shock are computed as:

\[ ASY_{h,r,t}^{+-} = GR_{h,r,t}(v^{(r)}) + GR_{h,r,t}(-v^{(r)}). \]

The larger are the differences between responses to positive and negative shocks, the larger is \( ASY_{h,r,t} \) (in absolute value). We modify the algorithm described in section 2.3.1 to compute \( ASY_{h,r,t}^{+-}(reg1) \) in step 3 and \( ASY_{h,r,t}^{+-}(reg2) \) in step 4. This implies we aim to compute:

\[ ASY_{h,r}^{+-}(reg1) = 1/T_1 \sum_{t=1}^{T_1} \left[ GR_{h,r,t}^{(reg1)}(v_1^{(r)}) + GR_{h,r,t}^{(reg1)}(-v_1^{(r)}) \right] \]
\[ ASY_{h,r}^{+-}(reg2) = 1/T_2 \sum_{t=1}^{T_2} \left[ GR_{h,r,t}^{(reg2)}(v_2^{(r)}) + GR_{h,r,t}^{(reg2)}(-v_2^{(r)}) \right] \]

As in the case of the responses, we compute 68% confidence bands for each asymmetry measure at horizons \( h = 1, \ldots, H \). These bands are employed to assess whether positive and negative shocks have statistically different effects by evaluating whether either \( ASY_{h,r}^{+-}(reg1) \) or \( ASY_{h,r}^{+-}(reg2) \) are nonzero.

We also consider asymmetries from the size of the shock. The shocks implied by the impact vector \( v_1^{(r)} \) and \( v_2^{(r)} \) are equivalent to one-standard deviation shocks, so we call these shock as "small". We consider two-standard deviation equivalent impacts \( 2v_1^{(r)} \) and \( 2v_2^{(r)} \) as large shocks. We measure asymmetries for the size of shock conditional on each one of the regimes at the impact as:

\[ ASY_{h,r}^{ls(reg1)} = 1/T_1 \sum_{t=1}^{T_1} \left[ GR_{h,r,t}^{(reg1)}(2v_1^{(r)}) - 2 \times GR_{h,r,t}^{(reg1)}(v_1^{(r)}) \right] \]
\[ ASY_{h,r}^{ls(reg2)} = 1/T_2 \sum_{t=1}^{T_2} \left[ GR_{h,r,t}^{(reg2)}(2v_2^{(r)}) - 2 \times GR_{h,r,t}^{(reg2)}(v_2^{(r)}) \right]. \]
If large shocks have different effects from small shocks in, say, regime 2, we expect that \( \text{ASY}_{b,s}^{(reg2)} \) will be nonzero for a set of horizons and shocks. As before, we use different draws from the posterior distribution of the parameters to compute 68% confidence bands for these asymmetry measures as the main values are obtained using the median as described in section 2.3.1.

### 2.4 Choosing 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.

In our empirical application, we assume the economy is driven by four factors: a real factor, a nominal factor, a monetary factor, and credit factor. This choice was mainly driven by economics considerations since it aids the identification of four common structural shocks.⁹

Next, we formally identify which one of the four factors is the best candidate to be the transition variable. Since the marginal data density of the model is not available in closed form, we rely on the Bayesian information criterion (BIC). Assuming that \( \theta \) is the vector of all the model parameters, such that \( \ln f(\theta) \) is the log-likelihood value at a given set of parameters \( \theta \), where \( y = \{Y_t\}_{t=p+1}^T \), the BIC is then

\[
BIC = -2E_\theta[\ln f(\theta)] + \ln(T - p)[2NRp + N - R],
\]

where \( E_\theta[\ln f(\theta)] \) 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 the maximization of the average likelihood.

### 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 regime changes in the dynamic relationships among economic variables? Second, do they amplify the effects of economic shocks? Third, do they generate sign/size asymmetries in the effects of economic shocks?

⁹To 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.
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 Băńbura 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 in 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. Brunnermeier 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.\(^\text{10}\)

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

\(^{10}\)The first variable in each block, as described in Table 1, has the loading parameter in $B_0$ equal to 1. This normalization imposed in the matrix $B_0$ was first suggested by Reinsel (1983).
Table 2, we use the factors computed at the posterior mean using the MAI model.\textsuperscript{11}

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, with all the proper signs. 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.

\subsection*{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 four different ST-MAI model specifications. They vary by the choice of factor to act as transition variable.\textsuperscript{12}

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 2A shows the values of the transition function using the credit factor as transition variable $[\Pi_p(\gamma, c, g_{t-1}^{(4)})]$ 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 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.

Figure 2B presents the transition function at the posterior mean against the sample values of the transition variable, $g_t^{(4)}$. We can clearly observe that there are many data points between 0 and 1, indicating that a smooth transition is well supported by the data.

\textsuperscript{11}The model is estimated as described in section 2.1 with 20,000 draws where the first 4,000 are discarded for the computation of the posterior mean.

\textsuperscript{12}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.
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 the credit conditions at the time of the shock can also lead to the amplification of shocks. Specifically, we evaluate the responses to structural shocks of six key indicators selected from the 20 variables in Table 1. 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. We checked whether the effects of credit shocks are robust to changing the ordering between monetary and credit factors. We find that our median estimated values of the effects of credit shocks at impact change very little when we change the ordering.

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 credit stress regime (regime 2), while responses in blue assume the shock hits in the low credit stress regime (regime 1). Impact responses \( (h = 1) \) may change over regimes because the variance-covariance

\(^{13}\)Responses for all other variables are available upon request.
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 (2017): 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 either positive and negative shocks or large and small shocks have different effects. Before showing the results for the asymmetry measures described in section 2.3 \((ASY^{++}(reg1), ASY^{+-}(reg2), ASY^{ls(reg1)}, ASY^{ls(reg2)})\), we use differences in the probability of regime changes after the shock as a first glance on the issue of different responses depending on the size and the sign of the shock. Table 4 presents the
probability of staying in the same regime as the one at impact over a 12-month period after the shock. Recall that in the ST-MAI model the variables that trigger regime changes are endogenous so that, even if a shock hits the economy during the low stress regime, there is a probability that after one year the economy switches to the high stress regime. Table 4 explores the effect of different sizes and signs of the shock on this probability, based always on the same set of histories at the time of shock. We consider our four identified structural shocks for cases they are either positive or negative and are small (equivalent to one-standard deviation) and large. The results in Table 4 clearly show that the size and the sign of the shocks have virtually no effect on the likelihood to switch to the high stress regime when at the time of the shock the model is in the low credit stress regime. Because the low stress regime covers 80% of the period, this suggests that normally positive and negative shocks and small and large shocks have very similar effects. However, during the high stress regime, good shocks (positive demand shock, negative supply shock, loosing of monetary policy stance and decrease in credit spreads) increase the likelihood of moving out of the high credit stress regime. Because the transition variable measures credit conditions, a large shock improving credit conditions (-2σ) delivers a probability of switching to the low stress regime of 42%, while this probability is of only 18% if we change the sign of the shock. These results suggest that the duration of the high credit stress regime depends on the shocks hitting the economy once we are in the high stress regime. It is reassuring that loosing the monetary policy improves the probability of regime switching to 36% after one year.

Next, we compute the asymmetry measures described in section 2.3 for all the 20 variables in the VAR and for each of the four common shocks. We use 68% confidence bands to assess whether there are statistically significant asymmetries. For responses computed to shocks in the low credit stress regime at impact, we find no evidence of significant asymmetry. Figure 7 shows estimates of \( \text{ASY}_{h,r}^{ts(\text{reg2})} \) for the unemployment, the fed fund rate and the commercial paper spread as responses to each of our four common shocks and for \( h = 1, \ldots, 24 \). We choose these variables because they are the ones that normally exhibit asymmetries during the high credit stress regime. Figure 7 indicates that positive and negative demand shocks have symmetric effects, but supply, monetary policy and credit shocks have asymmetric effects, that is, large shocks have disproportionate stronger effects than small shocks. A large shock to credit spreads increases significantly more unemployment even though the fed funds rate downward movement is disproportionately larger. This might be explained by the stronger effects on commercial
paper spread, which measures short run corporate market riskiness. These results suggest that
the size of the shock matters if the economy is in a credit stress regime. They support the
theoretical implications discussed in Krishnamurthy and Muir (2017) but also add evidence
that it is not only financial shocks that generate asymmetric effects, but also inflationary and
monetary policy shocks.

Figure 8 shows estimates of $ASY_{h,r}^{+-(reg^2)}$ for unemployment and commercial paper spread. There are sign asymmetries for large (two-standard deviation) shocks. Figure 8A shows estimates as responses to supply shocks, and the following figures present values for monetary policy and credit shocks. Figure 8C shows industrial production instead of unemployment so we can compare our results with Barnichon et al. (2017). 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 $ASY_{h,r}^{+-(reg^2)}$ 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. In Figure 8D 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.

The detected asymmetries in the response of unemployment to shocks imply that unem-
ployment 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.

Barnichon et al. (2017) empirical results suggest that shocks that improve credit supply
(negative shocks in our case) have muted effects on industrial production while shocks that
contract credit supply have strong negative effects on industrial production. Their effects were
computed using a nonlinear projection approach, assuming that responses differ depending on
the sign of the past shocks. Our results suggest that an unexpected improvement in credit
conditions may have a stronger effect in increasing growth than a deterioration would have if
at the time of the shock we are in the high credit stress regime. These dissimilar results can be reconciled if we consider the responses in Figure 5 of Barnichon et al. (2017) as regime-dependent responses for a high stress regime (credit supply contraction) and for a low stress regime (credit supply expansion). This is a reasonable assumption if we consider that positive credit supply shocks are more likely during the low stress regime and negative credit supply shocks are more likely in the high stress regime. Their responses are then similar to the ST-MAI responses to credit tightening shocks in Figure 6. The flexibility of the impulse response analysis based on the ST-MAI model allows us to better understand what it is really driving changes in the transmission of credit shocks, and how US data support the implications of theoretical models as summarized by Krishnamurthy and Muir (2017).

3.4 Does the use of a large model matter?

We claim in the introduction of this paper that by including more variables in a VAR, we enlarge the information set employed to compute impulse responses and that this might be beneficial for structural analysis, as it alleviates omitted variable bias and permits a more granular analysis of the effects of the shocks. In this subsection we estimate a smooth transition VAR with five variables to check if we are able to replicate our main empirical results with this smaller model. The five variables described in Table 1 that we included in this small VAR are: industrial production, unemployment, CPI, fed fund rate (+ shadow rate) and the EBP credit spread measure. The model is as in Barnichon et al. (2017), except that we include unemployment. We estimate the ST-VAR using MCMC blocks 1 to 3 of the estimation procedure described in section 2.2. As before, we use the data transformations in Table 1 and $p = 13$. We use the EBP as transition variable.

Figure 9 shows the estimated regime changes. The correlation with the regime changes estimated in Figure 3 is of only 58%. There is a longer upper regime between 2000 and 2003 and the upper regime lags the NBER recession in 2008. We compute the BIC for this model using the average likelihood and compare it with the BIC for the ST-MAI model for the fit of the five variables included in the small ST-VAR model. The BIC supports the ST-MAI model even if it estimates fewer parameters than the ST-VAR (when $R = 4$) if we consider only the parameters of the five equations considered.

We use a Cholesky decomposition to identify the shocks, using the variable ordering above. Figure 10 presents (cumulative) responses with 68% bands for the upper and the lower regime
at the time of shock. We compute responses for IP (activity) shocks, CPI (inflation) shocks, Fed rate (monetary policy, MP) shocks and EBP (credit) shocks. This exercise is designed to be comparable with Figures 3 to 6. In general, the responses to inflation and credit shocks are similar to the responses computed with the large ST-MAI model, while responses of activity and MP shocks are very different (the response to MP shocks does not change with credit conditions!). We conclude that, even though in this application one does not necessarily need a large model to measure the effects of credit shocks, the large MAI model helps to capture the effects of other important shocks by enlarging the information set employed in the computation of the responses, and it also permits to assess the effects of the shocks on a larger number of variables.

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 and size asymmetries, so that positive and negative shocks of the same size can have different effects (in absolute value) and small and large shocks of the same sign can also have asymmetric effects.

Our empirical results suggest that the duration of financial fragility episodes depends crucially on the type, size and sign of the shocks hitting the economy. Episodes can be shorter if large good shocks hit the economy. Fortunately, policy makers are able to control one of these good shocks – the monetary policy shock – and we are able to show that by loosening the monetary policy stance, policy makers increase the probability of moving out from a financial stress episode after one year.

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 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 changes across regimes. In this sense, the model is more flexible than a FAVAR, which instead assumes constancy of parameters across different regimes.

References


A Detailed Algorithm to Compute Responses

The algorithm to compute generalised responses conditional on a specific regime at the impact, including confidence bands, is described below.

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

2. Using the transition function $\Pi_t(\gamma^{(j)}, e^{(j)}, x^{(j)}_{t-1})$, define the set of regime 1 and regime 2 histories ($I_{t}^{(\text{reg}1)}$ and $I_{t}^{(\text{reg}2)}$).

3. Using the $A^{(j)}$, $B^{(j)}_0$, $\Sigma^{(j)}$, $\gamma^{(j)}$, $e^{(j)}$ 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 $\hat{Y}^{(r)}_{t+1|v^{(r)}_1}, ..., \hat{Y}^{(r)}_{t+h|v^{(r)}_1}$ and $\hat{Y}^{(r)}_{t+1}, ..., \hat{Y}^{(r)}_{t+h}$ for each set of histories. These paths are obtained by simulating the system using draws from $e^{(k)}_{t+h} \sim N(0, \Sigma^{(k)}_{t+h|v^{(r)}})$. This implies that we simulate paths also for $\Sigma^{(k)}_{t+1|v^{(r)}}, ..., \Sigma^{(k)}_{t+h|v^{(r)}}$ 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.
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 step 3 but using the shock $v_2^{(r)}$ for each history $t = 1, \ldots, T_2$. 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 $j = 1, \ldots, J$.

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


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

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

Note: The sample period is 1974M1-2016M8, but observations between 1974M1 and 1982M2 are employed as pre-sample. We normalised the transformed time series of each variable before estimation.
Figure 1: Factors as estimated with a MAI Model.

Note: Monetary policy factor in the right axis. Factors are transformed to annual differences. The MAI model is estimated with R=4 using the 20 variables in Table 1. The first variable in each block has the loading parameter in \( B_0 \) set to 1, all other parameters, when not constrained to zero because the variable does not enter a specific factor, are estimated as described in section 2.2.
Table 2: Correlations among and with MAI estimated factors

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>F_activity</td>
<td>0.06</td>
<td>0.61</td>
<td>-0.47</td>
<td>0.86</td>
<td>-0.39</td>
<td>-0.02</td>
</tr>
<tr>
<td>F_inflation</td>
<td>1</td>
<td>-0.13</td>
<td>0.48</td>
<td>-0.11</td>
<td>0.54</td>
<td>0.12</td>
</tr>
<tr>
<td>F_mp</td>
<td>-0.13</td>
<td>1</td>
<td>-0.49</td>
<td>0.63</td>
<td>-0.34</td>
<td>-0.07</td>
</tr>
<tr>
<td>F_credit</td>
<td>0.48</td>
<td>-0.49</td>
<td>1</td>
<td>-0.51</td>
<td>0.78</td>
<td>0.53</td>
</tr>
</tbody>
</table>

Note: These are computed using factors estimated with the MAI model applied to the variables in Table 1. These are computed for the factors displayed in Figure 1.

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

<table>
<thead>
<tr>
<th></th>
<th>Average Likelihood</th>
<th>BIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>F_activity as trans. var.</td>
<td>-7820.760</td>
<td>28271.735</td>
</tr>
<tr>
<td>$\lambda_1=1; \Delta \Sigma=25/110; \Delta \gamma_c=0.01$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>F_inflation as trans. var.</td>
<td>-8004.157</td>
<td>28638.529</td>
</tr>
<tr>
<td>$\lambda_1=1; \Delta \Sigma=120/20; \Delta \gamma_c=0.01$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>F_mp as trans. var.</td>
<td>-7859.639</td>
<td>28349.943</td>
</tr>
<tr>
<td>$\lambda_1=1; \Delta \Sigma=20/120; \Delta \gamma_c=0.01$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>F_credit as trans. var.</td>
<td>-7749.376</td>
<td>28128.967</td>
</tr>
<tr>
<td>$\lambda_1=1; \Delta \Sigma=120/20; \Delta \gamma_c=0.01$</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: All specifications with 4 factors as described in Table 1. The Table also indicate hyperparameters as discussed in section 2.2, which were 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 Transition Variable.

Figure 2A: Transition function over time

Figure 2B: Transition function at posterior mean parameters against estimated values of F_credit
Figure 3: Responses to a negative demand shock computed with the ST-MAI model

Note: Dotted lines are 68% confidence bands.
Figure 4: Responses to a positive supply shock computed with the ST-MAI model

Note: Dotted lines are 68% confidence bands.
Figure 5: Responses to a positive monetary policy shock computed with the ST-MAI model

Note: Dotted lines are 68% confidence bands.
Figure 6: Responses to a positive credit spread shock computed with the ST-MAI model

Note: Dotted lines are 68% confidence bands.
### Table 4: Probability of staying at the regime at the impact of the shock over a 12-month period after the shock

<table>
<thead>
<tr>
<th>Regime at time of the shock:</th>
<th>Low Stress Regime</th>
<th>High Stress Regime</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Positive shocks</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Type of shock:</strong></td>
<td><strong>Small ($v_1$)</strong></td>
<td><strong>Large (2$v_1$)</strong></td>
</tr>
<tr>
<td>Demand (activity) shock</td>
<td>0.96</td>
<td>0.96</td>
</tr>
<tr>
<td>Supply (price) shock</td>
<td>0.95</td>
<td>0.95</td>
</tr>
<tr>
<td>Monetary policy shock</td>
<td>0.95</td>
<td>0.95</td>
</tr>
<tr>
<td>Credit (spread) shock</td>
<td>0.94</td>
<td>0.93</td>
</tr>
<tr>
<td><strong>Negative shocks</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Type of shock:</strong></td>
<td><strong>Small (-$v_1$)</strong></td>
<td><strong>Large (-2$v_1$)</strong></td>
</tr>
<tr>
<td>Demand (activity) shock</td>
<td>0.96</td>
<td>0.96</td>
</tr>
<tr>
<td>Supply (price) shock</td>
<td>0.96</td>
<td>0.97</td>
</tr>
<tr>
<td>Monetary policy shock</td>
<td>0.96</td>
<td>0.96</td>
</tr>
<tr>
<td>Credit (spread) shock</td>
<td>0.97</td>
<td>0.98</td>
</tr>
</tbody>
</table>

Note: These are the proportion from the total number of horizons ($h=1,...,12$) that we do not observe regime changes as response for each specified shock. These are computed with parameters at the posterior mean and using 200 usual shock draws ($K=200$ in section 2.3) to compute the conditional expectation after the shock.
Figure 7: Asymmetries between responses to large (2*v) and small (v) shocks in the high stress regime.

7A: Demand (activity) shocks.

7B: Supply (price) shocks

7C: Monetary Policy shocks

7D: Credit Spread shocks

Note: Dotted lines are 68% confidence bands. These are size asymmetries as defined in section 2.3.1.
Figure 8: Asymmetries between responses to positive (2*v) and negative (-2*v) shocks in the high stress regime

Figure 8A: Supply (prices) shocks

Figure 8B: Monetary Policy shocks

Figure 8C: Credit Spread shocks
Figure 8D: Responses to a small supply shock in the high stress regime

Note: Dotted lines are 68% confidence bands. These are sign asymmetries as defined in section 2.3.1.
Figure 9: Regime changes in small ST-VAR model with EBP as Transition Variable.

Note: The small ST-VAR model has five endogenous variables: IP, UNEM, CPI, FedRate (+shadow), EBP. There are no common factors in this model.
Figure 10: Responses computed with the small ST-VAR model.

Figure 10A: Responses to negative IP shocks

- **IP**
- **Unemp**
- **CPI**
- **EBP**
- **Fed rate**
Figure 10B: Responses to positive inflation shocks
Figure 10C: Responses to positive Fed fund rate (Monetary Policy) shocks
Figure 10D: Responses to positive EBP (credit spread) shocks

- **IP**
- **Unemp**
- **CPI**
- **EBP**
- **Fed rate**

**Legend:**
- lower regime
- upper regime