Credit Conditions and the Asymmetric Effects of Monetary Policy Shocks*

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Abstract

To assess whether and how the effects of monetary policy shocks depend on credit market conditions, we introduce endogenous regime switching in the parameters of a Multivariate Autoregressive Index model. We develop a Bayesian framework to estimate dynamic responses to structural shocks using the proposed nonlinear vector autoregressive model applied to a large number of endogenous variables. The computed responses of economic activity and prices to monetary policy tightening/easing and large/small shocks are asymmetric. And these asymmetries are explained by the effect of monetary policy shocks on credit conditions and the probability of regime changes.

Keywords: Credit conditions; Multivariate Autoregressive Index models; Smooth Transition; Bayesian VARs, external instruments.

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

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1 Introduction

Currently, there is 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, and lead to a decline in economic activity, e.g., Gilchrist and Zakrajsek (2012), Faust, Gilchrist, Wright and Zakrajsek (2013) and Lopez-Salido, Stein and Zakrajsek (2017). In addition, financial shocks that hit the economy in periods of credit stress may have different effects on macroeconomic variables (Galvao and Owyang, 2018). In this paper, we evaluate how the impact and the transmission of monetary policy shocks depend on credit conditions. Caldara and Herbst (2019) provide evidence of the role of the contemporaneous effect of monetary policy on credit spreads to the dynamic transmission of monetary policy shocks. They identify monetary policy shocks with the aid of a proxy, which is based on the high-frequency reaction of future markets to monetary policy announcements, as in Gertler and Karadi (2015). Miranda-Agrippino and Ricco (2018) improve the high-frequency proxy by removing market surprises caused by new information regarding the prospects of the economy, such as monetary policy authority forecasts updates. We identify the impact effects of monetary policy shocks using both the high-frequency proxies employed by Gertler and Karadi (2015) and by Miranda-Agrippino and Ricco (2018).

Our main contribution is to measure changes in the impact and the transmission of monetary policy shocks using a nonlinear vector autoregressive model. A popular method to capture regime changes in macroeconomic dynamics is the application of a Markov-switching model, as surveyed by Hamilton (2016). We choose instead to use a smooth transition model, previously applied to find regime changes in the transmission to monetary policy shocks (Weise, 1999), fiscal shocks (Auerback and Gorodnichenko, 2012) and financial shocks (Galvao and Owyang, 2018). As the dynamic transmission of shocks may change at each point in time, the advantage of smooth transition models is that these recorded changes are smooth over time, since the transmission relies on time-varying weights applied to the estimated dynamic coefficients in the upper and lower regimes. These smooth changes are in contrast to the abrupt changes implied by Threshold and Markov-Switching models. Another advantage of smooth transition models is that a combination of observed variables leads to regime changes, with a clear identification of the forces behind the switching. In contrast, the nonlinear projection approach in Barnichon and Matthes (2018) employs the sign of past structural shocks to describe changes in the shock transmission. Finally, smooth transition models can nest threshold models, including the specification by Balke (2000) applied to evaluate the impact of short-term credit risk as a nonlinear propagator of shocks.

Typically, benchmark vector autoregressive models employed to measure the dynamic effects of monetary policy shocks include a small set of variables (Gertler and Karadi, 2015). Of interest is to allow for broad information set to estimate the dynamic responses as in Miranda-Agrippino and Ricco (2018) or, in a factor-augmented VAR context, in Gilchrist, Yankov and Zakrajsek (2009). In this paper, we consider a large VAR model including eight different monthly measures of economic activity, four measures of aggregate prices, two measures of the short-term rate, and six measures of credit conditions.

To deal with the dimensionality issue, we employ a Multivariate Autoregressive Index (MAI) VAR representation, which was first proposed by Reinsel (1983) and extended by Carriero, Kapetanios and Marcellino (2016) to allow for Bayesian analysis.[1] The advantage of the MAI approach is that a small set of common shocks drives the dynamics of a more extensive set of endogenous variables. By using estimates of the reduced-form common shocks and a proxy for monetary policy shocks, we show how to measure the impact of monetary shocks on all endogenous variables.

Our proposed approach exploits the dimensionality reduction warranted by the MAI approach to be able to model nonlinear dynamics for a large set of endogenous variables. 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 common observable 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. As regime changes are a function of endogenous variables, the probability of moving out from the current regime may change as a response to shocks. A consequence is that the proposed modelling provides evidence of asymmetric effects from easing relative to tightening of monetary policy as in Barnichon and Matthes (2018) and Angrist, Jorda and Kuersteiner (2018). These asymmetric effects, however, are explained by how easing and tightening monetary policies affect credit conditions and the probabilities of regime changes differently.

We develop Metropolis-in-Gibbs algorithms to estimate the smooth transition MAI (ST-

[1] 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.

MAI) model. In contrast with factor-augmented VAR specifications as in Galvao and Owyang (2018), the ST-MAI model does not require filtering to obtain the set of unobserved factors, avoiding computational issues from a nonlinear filtering step in the estimation. We follow Lopes and Salazar (2005) and Galvao and Owyang (2018) to draw the parameters of the smooth transition function jointly in a Metropolis step, that is, the parameters of the transition function are estimated using available data (in contrast to Aikman, Lehner, Liang and Modugno (2017)). For the regime-conditional variance-covariance matrix, we use a variation of the inverse-Wishart proposal approach in Galvao and Owyang (2018). We use the method proposed by Carriero et al. (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 (2019) to reduce further the computational time caused by a 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, short-rates and credit conditions. Based on ST-MAI coefficients posterior distributions, we can compute dynamic responses to shocks for all 20 endogenous variables and also for the small set of factors. As the factors are linked to a variable grouping defined by an economic concept, the modelling allows us to be agnostic about how to measure vital economic variables such as economic activity, prices, the short-rate and credit conditions.

We find evidence (based on a measure of fit applied to different specifications) that changes in the dynamics link between macro and financial variables are characterized by recurrent regime changes triggered by the credit factor. We measure the effects of factor loadings restrictions on how the model fits the data to support our specification choice.

The empirical results suggest significant asymmetries related both to credit conditions and to the size and sign of the monetary shocks. In particular, decisive monetary policy easing during a period of weak credit conditions can lead to disproportionate positive effects on economic activity and inflation. These disproportionate effects are caused by how the policy affects credit conditions over time, leading to a switch to the lower regime, where monetary policy has the expected effects on economic activity and inflation. This novel empirical evidence, obtained with a nonlinear VAR model for a broad set of endogenous variables, highlights how monetary policy can be crucial for macroeconomic stabilization during periods of credit market turmoil.

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 look for amplification effects and asymmetries in the dynamic effects of monetary policy shocks. 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 monetary shocks depending on credit conditions. After introducing the model, we consider (Bayesian) estimation and structural analysis.

2.1 The ST-MAI model

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

$$Y_t = c_0 + \sum_{u=1}^{p} C_u Y_{t-u} + \varepsilon_t, \tag{1}$$

with $\varepsilon_t \sim i.i.d.N(0, \Sigma)$, $t = 1, ..., T$, and c_0 an $N \times 1$ vector of intercepts. The number of the VAR(p) parameters grows proportionally to N^2 as p increases, leading quickly to a number that is 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. 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:

$$Y_t = a_0 + \sum_{u=1}^{p} A_u B_0 Y_{t-u} + \varepsilon_t, \tag{2}$$

or

$$Y_t = a_0 + \sum_{u=1}^{p} A_u F_{t-u} + \varepsilon_t, \tag{3}$$

where

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

The R variables in F_t can be considered as observable factors (indices), driving the dynamics of the variables in Y_t. We discuss how we name the factors by imposing restrictions on B_0 in the next subsection. 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 regime changes in the parameters even when N is large.

Assume now that the parameters $a_0, A_1, ..., A_p$ change smoothly with the regime. Hence, a smooth transition MAI model (ST-MAI) is:

$$Y_t = a_0 + \psi_t(\gamma, c, x_{t-1})d_0 + \sum_{u=1}^{p} A_u F_{t-u} + \sum_{u=1}^{p} \psi_t(\gamma, c, x_{t-1}) D_u F_{t-u} + \varepsilon_t, \tag{5}$$

where $\psi_t(\gamma, c, x_{t-1})$ is a logistic function, x_t is the transition variable, c is the threshold, and γ is the smoothing parameter.[2] The model implies that if the transition variable x_{t-1} is large in comparison with the threshold c, the value of the scalar $\psi_t(\gamma, c, x_{t-1})$ 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, $\psi_t(\gamma, c, x_{t-1})$ gets close to 0, and the coefficients are A_u. This means that D_u measures the difference in conditional mean dynamics between regimes. The intercept also changes with the regime as the vector d_0 measures the differences between regimes. This feature allows for regime-changes in the unconditional mean of Y_t, which is an essential feature of regime changes in macroeconomic variables, as suggested by Hamilton (2016). 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 the key drivers to describe the dynamics in the variables in Y_t. Hence, we have:

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

[2] For surveys on smooth transition VARs, see Van Dijk, Terasvirta and Franses (2002) and Hubrich and Terasvirta (2013).

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

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

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 model dynamics. We use single factors so that we can establish the key driver of regime changes empirically.[3]

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:

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

to capture regimes with longer duration and avoid picking up outliers. A similar smoothing is used, for example, in Auerback and Gorodnichenko (2012). Even though these regime changes are not based on all past history of observables as in the case of Markov-Switching Models (Hamilton, 2016), the persistence of the transition variable implies that the memory of a set of observables is considered as $g_{t-1}^{(r)}$ drives regime changes. The advantage of ST-MAI modelling is that we can easily interpret the drivers behind regime changes without the need for a filtering step in the estimation procedure.

We model the error variance of the $N \times 1$ vector of reduced-form disturbances ε_t as follows:

$$Var(\varepsilon_t) \equiv \Sigma_t = (1 - \psi_t(\gamma, c, x_{t-1}))\Sigma_1 + \psi_t(\gamma, c, x_{t-1})\Sigma_2, \tag{8}$$

where $\psi_t(\gamma, c, x_{t-1})$ is the logistic function as in (6). The specification implies that if the value of $\psi_t(\gamma, c, x_{t-1})$ is near zero, then the variance-covariance matrix is near Σ_1, but if the value of $\psi_t(\gamma, c, x_{t-1})$ 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 factors, $g_t^{(r)}$. Note that we have just one transition function, $\psi_t(\gamma, c, x_{t-1})$, 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, Car-

[3]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.

riero et al. (2019) allow the variances to change over time (diagonal of Σ_t), while covariances (elements outside the diagonal) are fixed. Our regime-dependent smooth transition specification is a parsimonious method to consider for covariance and variance changes over regimes, with possibly important consequences for the computation of dynamic responses.

2.2 Identification of Dynamic Causal Effects

The ST-MAI model described by equations (5), (6) and (8) can be applied to characterize regime changes when measuring responses to structural shocks. To characterize the nonlinear dynamic responses to structural shocks, we need first to identify the effect that the shock j has on the variable i ($i = 1, ..., N$) at the time $t = 1$ (impact). Then we need an approach to measure the dynamic effects of the shock. Because of the ST-MAI nonlinear dynamics, positive and negative shocks, or large and small shocks, may have asymmetric effects.

2.2.1 Measuring Impact Effects

As the ST-MAI model describes the dynamics of the endogenous variables using common observable and possibly correlated factors, a first step for the identification of the effect of structural shocks is the identification of the factors (Stock and Watson, 2016). We view the factors as a way of measuring an economic variable using many alternative observed measures. Each observable in the vector Y_t is a measure of one specific economic concept, say economic activity and aggregate price, which is summarized by one factor in the vector F_t. We divide the observed variables into groups, and then each group loads into a specific factor, implying we set the number of factors R as the number of groups and set zero restrictions in B_0 accordingly.[4]

Table 1 describes the variables we consider and the groupings. The activity group includes alternative measures of economic activity, as the inflation group includes four alternative prices indices. Next, we have two measures of the short-term interest rate that are used to identify monetary policy shocks in the literature. The first one is the policy rate. As our sample covers the zero-lower-bound period, we use the end-of-period effective fed fund rates, except for the months that the zero-lower-bound binds, for these we use the Wu and Xia (2015) shadow rate as published in the Atlanta Fed website. The second measure is the one-year Treasury bill, which was employed to measure the effects of monetary policy by Gertler and Karadi (2015). Finally, we consider six variables that have been reported in the literature as linked to credit conditions,

[4]The number of zero restrictions is sufficient to (over-) identify the B_0 and A_u matrices, $u = 1, ..., p$.

and that are available for an extended period (since 1974). This excludes most of the measures of supply of credit, but leads to the inclusion of credit spreads. We include measures of short (Commercial Paper and TED spreads) and long-term (excess bond premium and BAA spread) credit risk, in addition to housing credit risk (Mortgage risk) and term premium (term spread). This group of variables includes the excess bond premium computed using corporate bond yields by Gilchrist and Zakrajsek (2012), and credit spread measures that are part of the financial condition index in Hatzius, Hooper, Mishkin, Schoenholtz and Watson (2010) and of financial stress indices periodically released by regional Feds (Chicago, St. Louis and Cleveland). The credit group includes the 3-month commercial paper spread over the 3-month Treasury bill, which was employed as a transition variable by Balke (2000).

The zero restrictions in B_0 imply we can name the factors as activity, inflation, short-rates and credit. Following Carriero et al. (2016), we also impose a normalization restriction in B_0. We set the loadings of one observable in each group to be equal to 1, that is, $B_{0,ri} = 1$ for a specific observable i for each factor r, $r = 1, ..., R$. This means we define an arbitrary normalizing variable for each factor. We evaluate the robustness of our decision when applying this restriction to the credit group in the next section. Even though one variable only loads to one specific factor, the factors are correlated with each other because the macroeconomic and financial variables are usually correlated.[5]

The next step is to identify the R structural common shocks that drive the system, or a subset of interest. If we multiply equation (5) by B_0, we get:

$$F_t = B_0(a_0 + d_0\psi_t(\gamma, c, x_{t-1})) + B_0 \sum_{u=1}^{p} A_u F_{t-u} + B_0 \sum_{u=1}^{p} \psi_t(\gamma, c, x_{t-1}) D_u F_{t-u} + u_t, \quad (9)$$

with

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

The model in (9) is a smooth transition VAR for the observable factors F_t. This representation suggests that R common shocks (u_t) drive the joint dynamics of the N observables in the system.

Assume now that the reduced-form common innovations u_t are a linear combination of R

[5] Instead, in standard factor models the factors are unobservable and typically assumed to be contemporaneously uncorrelated.

structural shocks in the vector v_t.

$$u_t = H_t v_t.$$

We set $var(v_t) = I_R$, that is, a standard deviation normalization as defined by Stock and Watson (2016), and employed by Gertler and Karadi (2015) and Caldara and Herbst (2019). Note that the column vector $H_t^{(r)}$ measures the impact of one-standard-deviation change in shock j on each one of the r factors in F_t, $r = 1, ..., R$.

Based on a recursive identification, we could use a Cholesky decomposition of Ω_t to obtain H_t, that is, $\Omega_t = H_t H_t'$. Because Σ_t is constant within a specific regime (see eq. (8)), we could use $\Omega_{(reg)} = B_0 \Sigma_{reg} B_0'$ for $reg = 1, 2$ to obtain $H_{(reg)}$. However, Caldara and Herbst (2019) argue that this identification strategy could be inappropriate in this context due to possible contemporaneous correlation of the monetary and credit shocks. Hence, we consider an alternative approach, based on external instruments.

Specifically, we are interested in identifying a monetary policy shock, say $r = mp$, using an external instrument m_t. We compute $H_{(reg)}^{(r=mp)}$ for $reg = 1, 2$ following the approach in Gertler and Karadi (2015). As a consequence, we measure impact effects by employing $u_t^{(mp)}$ as a regressor to predict each one of the $R-1$ remaining commons shocks. These regressions are estimated by two-stage least squares, that is, using m_t as instrument for $u_t^{(mp)}$. We estimate the regression coefficients using the full sample available for the instrument as in Gertler and Karadi (2015). A final step to obtain $H_{(reg)}^{(mp)}$ is to apply the scaling method (such that $var(v_t) = I_r$) in Gertler and Karadi (2015) (page 18) using the regime-specific variance $\Omega_{(reg)}(= B_0 \Sigma_{(reg)} B_0)$. This last step implies that the impact vector $H_{(reg)}^{(mp)}$ changes with regime following the estimated regime-dependent variance-covariance matrices in (8), as expected based on the standard deviation normalization applied.

An alternative to our two-step approach is to compute $H_{(reg)}^{(r=mp)}$ using the proxy-VAR estimation approach in Caldara and Herbst (2019). As the time series of candidate proxies m_t typically start in the early 90's, we prefer the two-step approach such that we can estimate the parameters of the ST-MAI model over a more extended period, which better enables to capture regime changes.

Another possible modelling choice is to estimate regime-dependent impact effects that are not only due to changes in the variance of the shocks as we proposed earlier, but also due to the application of the two-stage-least-squares separately for each regime. Yet, empirically this alternative approach delivers monetary policy shocks impact effects that are qualitatively different from the ones described in Gertler and Karadi (2015) and Caldara and Herbst (2019). Because these differences may be due to the even shorter sample periods available for the estimation, we prefer to follow the literature and estimate impact effects using the sample period for which the proxy is available. As a consequence, our estimated dynamic responses may differ from the ones in the previous literature because of nonlinearities in the transmission of shocks but not because of instabilities in the monetary policy identification.

The advantages of applying the external instruments approach to reduced-form common innovations u_t instead of the original innovations ε_t are two. First, we are allowed to be agnostic about the adequate variable to measure the monetary policy innovations and monetary policy shocks. We are able to use both the policy rate and the one-year rate to measure the impact effects of monetary policy shocks based on a proxy. Second, even if part of the dynamics of the variables in Y_t is not explained by the set of common factors leading to serial correlation in ε_t, we find no evidence of serial correlation in u_t. This lack of serial correlation in reduced-form disturbances supports the assumption that the proxy is indeed exogenous to all remaining non-identified structural shocks.

Our ultimate interest, however, is to measure the impact effect of the common structural shock on the vector of endogenous variables Y_t. For this, it is convenient to apply the following decomposition to the reduced form shocks ε_t :

$$\varepsilon_t = \Sigma_t B_0' \Omega_t^{-1} u_t + B_{0\perp}' (B_{0\perp} \Sigma_t^{-1} B_{0\perp}')^{-1} \xi_t, \tag{10}$$

where u_t are the R (reduced form) commons shocks, ξ_t are $N - R$ idiosyncractic shocks, and $B_{0\perp}$ is an $N - R \times N$ matrix orthogonal to B_0 (as in Carriero et al. (2016)). The idiosyncratic shocks are orthogonal to the common shocks because, as $u_t = B_0 \varepsilon_t$ and $\xi_t = B_{0\perp} \Sigma_t^{-1} \varepsilon_t$, then $E[u_t \xi_t'] = B_0 \varepsilon_t \varepsilon_t' \Sigma_t^{-1} B_{0\perp}' = 0$. From equation (10), the regime-specific impact effects of a structural shock are:

$$\frac{\partial Y_{t+1}}{\partial v_{t+1}^{(r)}} = \Sigma_{reg} B_0' \Omega_{reg}^{-1} H_{(reg)}^{(r)} \text{ for } reg = 1, 2,$$

and we are particularly interested in $r = mp$, i.e., in the effects of the structural monetary policy shock. Note also that

$$\frac{\partial F_{t+1}}{\partial v_{t+1}^{(r)}} = B_0 \frac{\partial Y_{t+1}}{\partial v_{t+1}^{(r)}} = H_{(reg)}^{(r)},$$

implying that as we compute responses to all endogenous variables in Y_t, we can also obtain responses for their linear combinations included in F_t.

2.2.2 Measuring the Dynamic Transmission

Our primary interest is to measure asymmetries in the transmission of the structural shocks to observables in Y_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.

We define the response of all i variables at horizons h ($h = 1, ..., H$) from shock r computed using the history at time t as $IR_{t,h,r}$. The previous discussion suggests that the impact effect ($h = 1$) of a structural (common) shock (identified recursively or using an external instrument) r is:

$$\frac{\partial Y_{t+1|t}}{\partial v_{t+1}^{(r)}} = \Sigma_{reg} B_0' \Omega_{reg}^{-1} H_{(reg)}^{(r)} = \varpi_{(reg)}^{(r)} \text{ for } t \, \epsilon \, reg, \, reg = 1, 2. \tag{11}$$

For the following horizons, we compute responses as:

$$IR_{t,h,r} = \frac{\partial Y_{t+h|t}}{\partial v_{t+1}^{(r)}} = E[Y_{t+h}|I_t, \varpi_{(reg)}^{(r)}] - E[Y_{t+h}|I_t] \tag{12}$$
$$\text{for } h = 2, ..., H \text{ and for } t \, \epsilon \, reg, \, reg = 1, 2,$$

where $I_t = (Y_t', .., Y_{t-p+1}')'$. As a result, responses are computed by comparing endogenous variables paths over h horizons under two scenarios: a shock has hit with effect $\varpi_{(reg)}^{(r)}$ at $h = 1$ and no extra shocks (besides the usual ones) have affected the endogenous variables.

In both cases, K paths for Y_{t+h} are simulated, assuming I_t as initial values and using the parameters of the ST-MAI system in eq. (5) and eq. (8). These simulated paths are obtained using draws from $\varepsilon_{t+h}^{(k)} \sim N(0, \Sigma_{t+h}^{(k)})$ for $h = 2, ..., H$ where $k = 1, ..., K$.[6] The variance-covariance matrix $\Sigma_{t+h}^{(k)}$ 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 Σ_{t+h} is affected by the shock and may change as $h = 2, ..., H$. Hence, for each path k, Y values are simulated

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

using:

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

An implication of equation (12) is that we have one response function over horizons $h = 1,...,H$ at each point in time (I_t for $t = p+1,...,T$), since dynamic effects depend on the history at the time the shock hits. To visualize differences across regimes, 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 $\psi_{t+1}(\gamma,c,x_t) < 0.25$ for $t = p+1,...,T$, and $I^{(reg2)}$ as the history values such that $\psi_{t+1}(\gamma,c,x_t) > 0.75$.[7] Then the responses conditional on each regime at time t are:

$$
IR_{h,r}^{reg1} = 1/T_1 \sum_{t=1}^{T_1} IR_{t,h,r}^{(reg1)} \tag{13}
$$

$$
IR_{h,r}^{reg2} = 1/T_2 \sum_{t=1}^{T_2} IR_{t,h,r}^{(reg2)} \tag{14}
$$

where T_1 is the number of histories in regime 1 and T_2 is the equivalent for regime 2.

Responses may be accumulated. We accumulate the responses for each history, that is, we employ $IR_{t,h,r}$ for $h = 1,...,H$ to compute $CIR_{t,h,r}$ for all horizons before applying the regime-dependent averaging implied in (13) and (14).

The computation of the responses as equations (11) and (12) is for a given set of parameters values $(A_0^{(j)}, A^{(j)}, B_0^{(j)}, \Sigma_t^{(j)}, \gamma^{(j)}, c^{(j)}$ where $A = (A_1...A_p, D_1...D_p)'$ and $A_0 = (a_0, d_0))$. We use J equally-spaced values from the posterior distribution of the parameters to compute $IR_{h,r}^{reg1,(j)}$ and $IR_{h,r}^{reg2,(j)}$ with the aim of incorporating parameter uncertainty ($j = 1,...,J$).[8] Then our estimated responses to the structural shock $r = mp$ at regime 1 are the posterior median of $IR_{h,r}^{reg1,(j)}$ for $j = 1,...,J$, and confidence bands are computed using percentiles (16%, 84%) based on the same set of values $IR_{h,r}^{reg1,(j)}$. The complete algorithm for the computation of

[7] The stated thresholds (0.25 and 0.75) may exclude some between-regime histories depending on the smoothness of the transition function. These thresholds may be helpful to find sharper differences across regimes. In practice, empirical results are very similar when both thresholds are set to 0.5.

[8] We set $J = 400$ in the empirical application. Note that the computation of the posterior density for $IR_{h,r}^{reg1}$ and $IR_{h,r}^{reg2}$ is time consuming since we need to average over paths (K) and over histories (T_{reg}) for each set of parameters over the J draws.

these regime-dependent responses is described in Appendix A.

2.2.3 Measuring Asymmetries

In linear vector autoregressive models, the dynamic effects of monetary policy tightening and easing are symmetric. Also, the size of the shock affects the dynamic responses proportionally. Because of the nonlinear dynamics in the ST-MAI models, we may find asymmetries arising from both the sign and size of the shock. We evaluate these nonlinear dynamic effects in the next section, and here we describe how we measure asymmetries.

We consider responses to positive and negative shocks, and to large shocks. For example, if $H^{(mp)}_{(reg)}$ measures the impact of monetary policy tightening on the factors, then to assess the effects of monetary easing, we compute the following impact effects on the full set of observables:

$$IR_{t,h=1,(mp,neg)} = \Sigma_{reg} B_0' \Omega_{reg}^{-1} (-H^{(mp)}_{(reg)}) = \varpi^{(mp,neg)}_{(reg)} \ .$$

Similarly, we can consider the effects of larger policy changes as:

$$IR_{t,h=1,(mp,\varkappa)} = \Sigma_{reg} B_0' \Omega_{reg}^{-1} (\varkappa H^{(mp)}_{(reg)}) = \varpi^{(mp,\varkappa)}_{(reg)},$$

where if, for example, $\varkappa = 2$, we are interested in two-standard sized effects. The transmission is then computed as described earlier to obtain $IR_{t,h,r(neg)}$ and $IR_{t,h,r(\varkappa)}$ for $h = 2, ..., H$.

To measure asymmetries from the sign of the shock for a given history I_t, we compute:

$$ASY^{+-}_{t,h,mp} = IR_{t,h,(mp,pos)} + IR_{t,h,(mp,neg)}.$$

We modify the algorithm described in the Appendix to compute $ASY^{+-(reg1)}_{h,mp}$ in step 3 and $ASY^{+-(reg2)}_{h,mp}$ in step 4. This implies we aim to compute:

$$\begin{aligned} ASY^{+-(reg1)}_{h,mp} &= 1/T_1 \sum_{t=1}^{T_1} ASY^{+-}_{t,h,mp} \\ ASY^{+-(reg2)}_{h,mp} &= 1/T_2 \sum_{t=1}^{T_2} ASY^{+-}_{t,h,mp} \end{aligned}$$

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 positive and negative shocks have statistically different effects by evaluating whether either $ASY_{h,mp}^{+-(reg1)}$ or $ASY_{h,mp}^{+-(reg2)}$ are nonzero.

We also consider asymmetries from the size of the shock. As a consequence, we compute:

$$
\begin{aligned}
ASY_{h,mp}^{ls(reg1)} &= 1/T_1 \sum_{t=1}^{T_1} \left[\varkappa IR_{t,h,mp} - IR_{t,h,(mp,\varkappa)} \right] \\
ASY_{h,mp}^{ls(reg2)} &= 1/T_2 \sum_{t=1}^{T_2} \left[\varkappa IR_{t,h,r} - IR_{t,h,(mp,\varkappa)} \right].
\end{aligned}
$$

If large shocks have different effects from small shocks in, say, regime 2, we expect that $ASY_{h,mp}^{ls(reg2)}$ will be nonzero for a set of horizons. 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 earlier.

2.3 Estimation

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

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

where $\psi_t(\cdot) = \psi_t(\gamma, c, g_{t-1}^{(r)})$, and

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

$$
z_{t-1} = (1_N, \psi_t(\cdot)1_N)'
$$

and

$$
A_0 = (c_0, d_0)',
$$

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

$$
\begin{aligned}
Y_t &= z_{t-1}A_0 + Z_{t-1}A + \varepsilon_t \qquad (15) \\
var(\varepsilon_t) &= (1 - \psi_t(\cdot))\Sigma_1 + \psi_t(\cdot)\Sigma_2.
\end{aligned}
$$

The proposed algorithm includes three Metropolis steps in a Gibbs sampling approach. The algorithm has five blocks to obtain S posterior draws for all parameters. We obtain S draws, but we discard the first 20% before computing moments for the posterior density for each parameter.

The first block draws the parameters of the transition function similarly to Galvao and Owyang (2018). Conditional on previous draws of $\Sigma_1^{(s-1)}, \Sigma_2^{(s-1)}, A_0^{(s-1)}$, $A^{(s-1)}$ and $B_0^{(s-1)}$, we obtain a joint draw $\gamma^{(s)}, c^{(s)}$ using a Metropolis step, for $s = 1, ..., S$. 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 $g_t^{(r)}$. 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 $\gamma^{(s)}, c^{(s)}, A_0^{(s-1)}, A^{(s-1)}$ 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 (2018). 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 ones in the diagonal, and $pv_0 = N + 2$. The proposal distribution is $\Sigma_1^{-1} \sim W(C_1^{-1}, pv_1)$ with $pv_1 = pv_0 + \Delta_1 \sum_{t=1}^{T} I(g_{t-1}^{(r)} \leq c)$ [$I(.)$ is an indicator function] and $C_1 = \Delta_{\Sigma_1} \left[\sum_{t=1}^{T} e_{1t} e_{1t}'\right]$ where $e_{1t} = [1 - \psi_t(\gamma^{(s-1)}, c^{(s-1)}, g_{t-1}^{(r,s-1)})]\varepsilon_t^{(s-1)}$ and $\varepsilon_t^{(s-1)} = (Y_t - Z_{t-1}^{(s-1)} A^{(s-1)} - z_{t-1}^{(s-1)} A_0^{(s-1)})$. 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 $pv_2 = pv_0 + \Delta_2 \sum_{t=1}^{T} I(g_{t-1}^{(r)} > c))$ and $C_2 = \Delta_{\Sigma_2} \left[\sum_{t=1}^{T} e_{2t} e_{2t}'\right]$ where $e_{2t} = [\psi_t(\gamma^{(s-1)}, c^{(s-1)}, g_{t-1}^{(r,s-1)})]\varepsilon_t^{(s-1)}$. 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 $A^{(s)}$. Conditional on $\Sigma_1^{(s)}$, $\Sigma_2^{(s)}, \gamma^{(s)}, c^{(s)}$,

$A_0^{(s-1)}$ and $B_0^{(s-1)}$, we obtain a draw for $A^{(s)}$ from a multivariate Gaussian density implemented using the equation-by-equation procedure proposed by Carriero et al. (2019). The independent prior is Gaussian and the prior mean is zero for all values in A. The prior variance is set as:

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

We set the prior values for σ_i^2 equal to 1.

The fourth block draws the regime-dependent intercepts $A_0^{(s)}$. They are drawn from a multivariate Gaussian density conditional on values for $\Sigma_1^{(s)}$, $\Sigma_2^{(s)}, \gamma^{(s)}, c^{(s)}$, $A^{(s)}$ and $B_0^{(s-1)}$. The prior for each intercept is also Gaussian with mean zero and variance 4.

The fifth block draws the parameters employed in the computation of the factors. Conditional on $\Sigma_1^{(s)}$, $\Sigma_2^{(s)}, A^{(s)}, A_0^{(s)}$, $\gamma^{(s-1)}, c^{(s-1)}$, the draw $B_0^{(s)}$ is obtained using a random walk Metropolis step as described in Carriero et al. (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.

3 Credit Conditions and the Effects of Monetary Policy Shocks

3.1 Estimation and Specification of the ST-MAI model

The sample period is from 1974M1 up to 2016M8. Still, 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 required to obtain posterior draws for the factor loadings B_0. The 20 endogenous variables are described in Table 1, including the data transformation applied before values are normalized. The structural VAR literature on measuring dynamic effects of monetary policy typically employs activity and price variables in log-levels instead of monthly differences, as indicated in Table 1. Because it is unlikely that recurrent regime changes determine how the endogenous variables co-move in the long-run and they need to be led by stationary variables, we prefer to estimate the ST-MAI model with activity and prices variables in first differences. We then compute accumulated responses for all activity and price variables to be comparable with the results in the literature.

We set $p = 13$ and the hyperparameters of the prior are set as follows. The overall prior tightness is set to $\lambda_1 = \lambda_2 = 1$, so the priors do not impose strong restrictions on the dynamic parameters in A in equation (15). To aim at a 70% rejection rate, the transition function hyper-parameters are set as $\Delta_\gamma = \Delta_c = 0.01$ and the ones for the variance are set as $\Delta_{\Sigma_1} = 400$ and $\Delta_{\Sigma 2} = 1100$. We estimate the ST-MAI with 40,000 draws split over four chains to check for convergence. There were no convergence issues in our baseline specification. The baseline specification has the factor structure described in Table 1, with the credit spread as the transition variable, and the commercial paper spread as the variable with loadings normalized to 1 in the credit factor. We discard 20% of the initial draws, and use thinning to keep 4,000 draws of the saved posterior distribution. For each saved draw, we compute the likelihood as a measure of fit, which can be used for model comparison when the number of factors is fixed, as in our case, as the alternative models have the same number of parameters. Table 2 shows the average likelihood values.

We also consider the following alternative specifications. A specification with three factors instead of four, where the two short-term rates are included in the credit factor. A specification with four factors, but including the term spread in the monetary policy factor since recent monetary policy has attempted to affect the long-term rate. In both cases, the penalized fit (measured by SIC) deteriorates significantly in comparison to the baseline specification.

The alternative specifications in Table 2 provide evidence to support our choice of the baseline specification for the ST-MAI model. They include specifications that use the activity, the inflation and the short-rate factors as transition variable. There is clear evidence that they deteriorate fit. We also consider the effects of the loading normalization to one applied to different variables in the credit group, using the year-on-year transformation of the credit factor $g_t^{(4)}$ as transition variable. Table 2 shows the average likelihood for specifications for the estimated ST-MAI model after applying each possible normalization within the credit factor. The effect of the normalization is to change the scale of the estimated factor because of changes in the loadings values in B_0. Because the credit factor is then linked to the regime changes and the smooth transition parameters γ and c, the normalization affects the fit of the ST-MAI to the data even if hyper-parameters are kept fixed. It is clear from Table 2 that the normalization applied to commercial paper spread delivers the best fit, and avoids convergence issues (which emerge, for example, if loadings are normalized to the TED spread).

3.2 Factor Identification

Using the baseline ST-MAI specification, we compute the posterior median of the year-on-year factors over the estimation period (1982M3-2016M8). These are presented in Figure 1 over two panels. Then we compute the correlation with two alternative monthly indexes: the Philadelphia Fed Coincident Economic Activity index and the Chicago Fed Financial Condition Index. We find that the activity factor has an 86% correlation with the Philadelphia Fed activity index, and the credit factor has an 80% correlation with the Chicago Fed Financial Condition Index. The correlation between the short-rate factor and Financial Condition index is smaller at 45%. The advantage of the ST-MAI approach in comparison with the estimation of a VAR using these observed indexes is that we are able also to evaluate dynamic effects on individual variables, which could differ from the ones computed using the index.

The correlation analysis with external measures and the time series evolution of the factors described in Figure 1 suggest that the ST-MAI model delivers factor estimates able to characterize the common evolution of economic activity, inflation, short-rates and credit conditions. Inflation declines during periods of negative economic activity. Credit conditions tend to deteriorate as short-rates increase; however, credit conditions deterioration and improvements are faster and less smooth than short-rate changes.

3.3 Smooth Changes between Regimes

Figure 2A shows the values of the transition function using the credit factor as transition variable $[\psi_t(\gamma, c, g_{t-1}^{(4)})]$ at the posterior mean. The dotted lines are 68% confidence bands for the transition function, and the yellow line is the credit factor at the posterior mean. The Figure also includes NBER recession dates. The upper regime is identified for around 40% of the sample, including the months during the four NBER recessions. The upper regime extends after the end of the early 80's recession to cover the majority of the months during the 1980 decade.[9] Then the upper regime is identified again in the build-up to the 2001 and the 2008/9 recessions.

Figure 2B presents the transition function at the posterior mean against all the values that the transition variable, $g_t^{(4)}$, assumes over the 1982-2016 period. We can observe that the function assumes values between 0 and 1 for many data points, describing a smooth transition

[9] Similar regime chronology during the 1980's was presented by Galvao and Owyang (2018) with the Chicago Fed Financial Condition index as a transition variable to drive regime changes in a small VAR model.

from the lower to the upper regime at the end of the '90s and in 2006. Figure 2B also indicates a more significant dispersion of credit factor values in the upper regime than in the lower regime. As a consequence, we prefer not to rename the upper regime as the high-stress regime as in Galvao and Owyang (2018), but to call it as the weaker credit conditions regime.[10]

3.4 Dynamic Effects of MP shocks on factors

3.4.1 Instruments and Reduced-Form Shocks

Figure 3A presents two monetary policy shocks proxies: GK (Gertler and Karadi, 2013) and MAR (Miranda-Aggripino and Ricco, 2018). They are both computed using the high frequency effect of monetary policy announcements on the interest rates future markets. The main difference is that the MGR measure is cleaned out of effects caused by the new information on the economy provided by these announcements. Effects of surprises related to updates in Greenbook forecasts are removed. Miranda-Agrippino and Ricco (2018) argue that informational effects attenuate the negative effects of contractionary monetary policy on economic activity variables.

We also include in Figure 3A the posterior median estimate of the transition function over the period that both time series are available (1991 to 2012). It is clear that there are periods of smaller variabilities of these proxies (2004-2006 and 2010-2012) and that they usually coincide with the ST-MAI lower regime. There are also sometimes differences between the signs of the GK and MAR proxies, particularly evident during the last upper regime period (2007-2009).

Figure 3B presents the posterior median and 16% and 84% percentiles of the (common) short-rate innovation during the same period. An identification assumption is that the proxy in Figure 3A is able to explain some of the variation of the reduced-form innovation in Figure 3B. The proxy low variability periods seem to coincide with the ones observed for innovations. Figure 3B also helps to support the required identification assumption because of lack of serial correlation in the MP innovations (the average serial correlation across the considered draws is almost zero, with a standard deviation of 2%).

The ability of the GK instrument in identifying monetary policy shocks is discussed in Stock and Watson (2018). They provide evidence that the instrument is relevant using the

[10]Some of the alternative ST-MAI specifications considered in Table 2 deliver a higher discrepancy in the regimes frequency, including cases in which only 20% of the observations are classified in one of the regimes. However, as discussed, the likelihood values in Table 2 support this baseline specification.

first-stage F-stat if lags of the instrument and endogenous variables are included in the first-stage regression. Miranda-Agrippino and Ricco (2018) provide evidence of the relevance of their proposed instrument. We follow the literature assuming that both instruments are relevant instruments to identify monetary policy shocks. Our contribution is to employ the ST-MAI model to compute dynamic responses.

3.4.2 Dynamic Responses

Using the proxies in Figure 3 and the method described in section 2.2, we compute estimates of the responses of each factor to monetary policy shocks in each regime, using $J = 400$ equally-spaced values from the saved posterior distribution of the ST-MAI parameters. Responses are computed for all upper and lower regime histories identified using the transition function at each point in time, for the sample period 1982-2016. To obtain the responses in Figures 4 and 5, we first obtain simulated paths for the full vector of endogenous variables $Y_{t+1}, ..., Y_{t+h}$ as indicated in section 2.2, and then use B_0 estimates to obtain paths for $F_{t+1}, ..., F_{t+h}$, that is, we use $\left(\partial F_{t+h|t}/\partial v_{t+1}^{(mp)}\right) = B_0 \left(\partial Y_{t+h|t}/\partial v_{t+1}^{(mp)}\right)$. Based on the responses of the factors at each point in time, we average responses over each regime as described in section 2.2.

The advantage of measuring dynamic responses of monetary policy shocks to the factors is that we do not have to make a choice about which observed monthly indicator is best to measure the key economic variables (economic activity, inflation, short-rate and credit spreads). Of course, we are also able to compute specific responses for each endogenous variables, and we do so in section 3.7.

Figures 4 and 5 present the median and 16% and 84% quantiles of dynamic responses to a one-standard-deviation tightening of monetary policy. We present responses for horizons up to 48 months and each set of histories (lower and upper regimes). Figure 4 presents responses with monetary policy impact effects estimated using the GK instrument, and Figure 5 using the MAR instrument. The displayed responses for economic activity and prices are accumulated responses.

Results for the lower regime, that is, the periods when credit conditions are favorable, are in line with the previous literature (Gertler and Karadi, 2015; Caldara and Herbst, 2019; Miranda-Agrippino and Ricco, 2018). As a result of monetary policy tightening, economic activity declines at impact if using the MAR instrument, but it takes about a year to decline using the GK instrument. For both external instruments, we find that prices decline at impact as a result of a policy tightening. Median responses of credit to the monetary policy tightening at impact using the GK instrument are about 12 basis points larger than the ones computed using the MAR instrument. This decreased responsiveness of credit spreads to monetary policy using the MAR instrument may be caused by their removal of the effects of Fed forecast announcements from the high-frequency market reactions.

Impact effects computed for upper regime histories differ from the ones in the lower regime because of the estimated regime changes in the variance-covariance matrix of reduced-form shocks. However, even more notable are the changes in the dynamic responses in Figures 4 and 5. During the upper regime, short-rate responses are short-lived, and credit conditions responses are less persistent. Adverse effects on prices are more extensive and significant, but they have a faster reversion towards zero. Responses of economic activity are negative using the MAR proxy during the first year, but then revert to positive values in the second year. This dynamic reversal is smaller using the GK proxy, but then impact effects are significantly positive at short horizons and the medium-run negative effects are not observed as the dynamic transmission differs from the lower regime. Two comments apply. First, confidence bands are broad, and they include zero for most of the horizons so that one could claim no significant effects in economic activity in the upper regime. Second, the issue of counterintuitive effects of monetary policy at short horizons is one of the reasons that Miranda-Agrippino and Ricco (2018) propose to remove the effect of other announcements from the original GK instrument.

In the next section, we investigate additional characteristics of the dynamic effects of monetary policy shocks using the ST-MAI model and the GK and the MAR instrument by exploiting the effects of the sign and size of the shocks.

3.5 Changes in the transmission due to Sign Effects

Barnichon and Matthes (2018) provide evidence that expansionary monetary policy has weaker effects on unemployment than the equivalent contractionary policy, but stronger effects on inflation. They propose a methodology that approximates nonlinearities in the responses to monetary policy shocks for positive and negative shocks. By applying the ST-MAI modelling instead, monetary policy tightening and easing may lead to asymmetric dynamic effects because the probability of switching regimes changes as a response to shocks, and regimes are characterized by different dynamic linkages between economic and financial variables.

For example, in the first row of each panel of Table 3A, we display the posterior median estimate of the probability of being in the upper regime 24 months after a one-standard-deviation monetary policy shock. If the shock hits the ST-MAI model in the lower regime, a tightening shock, as the one displayed in Figures 4 and 5, leads to a 7-8% probability of switching to the upper regime (depending on the instrument). In contrast, an easing shock of similar size (that is, $-H^{(mp)}_{(reg)}$ instead of $H^{(mp)}_{(reg)}$ when computing $IR_{t,h=1,mp}$) leads to a 3% probability of switching. Because the dynamic coefficients differ across regimes, these differences in the probability of regime-switching due to the type of shock may lead to asymmetries in the responses to monetary policy tightening and easing. These differences also occur if the shock hits during the upper regime, the probability of staying in the weak credit conditions regime after a tightening shock is between 79 and 82% but following an easing shock is between 67% and 71%.

Because the credit factor values lead to regime changes, the probability of being in the upper regime after monetary policy tightening is more substantial using the GK instrument because of the estimated responsiveness of credit to monetary policy using the GK proxy. Similar reasoning explains the evidence that the probability of being in the upper regime following a policy easing is, in general, more significant using the MAR instrument.

Figure 6 presents the responses of economic activity and price factors to easing and tightening one-standard-deviation shocks hitting during the upper regime. During the upper regime, differences in the probability of regime changes after each type of shock vary between 8 to 16 percentage points depending on the proxy, so we are more likely to find asymmetries due to the sign of the shock. Similarly to Barnichon and Matthes (2018), we observe that expansionary shocks have flatter effects on economic activity (because the after one-year dynamic reversal is not as sharp) and more substantial effects on prices (that is, more persistent). The advantage of the application of ST-MAI model instead of the approach in Barnichon and Matthes (2018) is that we can provide a rationale for these asymmetric effects: tightening and easing the monetary policy have opposite effects on credit conditions which have nonlinear effects on the transmission of the shocks. As a consequence, we can link the evidence of the contemporaneous effects of monetary policy on credit conditions in Caldara and Herbst (2019) with the role of credit conditions to business cycles in Lopez-Salido et al. (2017).

3.6 Changes in the transmission due to Sign/Size Effects

Table 3 provides additional evidence to help us to evaluate asymmetric effects due to the sign and size of the monetary policy shock. The Table entries (except the first row in each panel) are the posterior median of each factor responses to monetary policy tightening and easing after 24 months. We present responses for shocks hitting in the lower and the upper regimes, and for both GK and MAR instruments. Table 3A presents responses to one-standard-deviation shocks (as in Figures 4, 5 and 6). In Table 3B, we display responses for four-standard-deviation shocks. The four-standard-deviation shock is computed by using $4H_{(reg)}^{(mp)}$ instead of $H_{(reg)}^{(mp)}$ as described in section 2.2.2. For the upper regime, the large shock impact effect on the short-rate is on average about 100 basis points, so the shock size is as the one in Miranda-Agrippino and Ricco (2018).

If there were no asymmetries from the sign of the shock, as in a typical linear VAR model, we would find tightening dynamic effects equal to easing effects in absolute values. It is evident in Table 3 that this is roughly the case during the lower regime for small shocks. For large shocks, even during the lower regime, we find dissimilarities for economic activity and prices responses. The probability of regime changes after a large shock is of 18 to 22% after policy tightening, but less than 1% after policy easing, explaining why we find sign effects for large shocks during the lower regime. Sign asymmetries are even more substantial for shocks hitting during the upper regime. During the upper regime, a tighter policy has more persistent effects on the short-rates.

Asymmetries from the size of the shock are identified by checking whether the responses on Table 3B are roughly four times the values in Table 3A. As in the case of the sign of the shock, a large shock may lead to a more substantial probability of regime-switching, leading to nonlinear effects in the transmission of shocks. A large easing shock increases the probability of switching out of the weak credit conditions (upper) regime. The probability of switching is about 65% using the GK instrument and 48% using the MAR instrument. This nonlinearity leads to disproportionately large positive effects on economic activity and inflation.

These empirical results suggest that decisive monetary policy easing during a period of weak credit conditions can lead to disproportionate positive effects on economic activity and inflation. These disproportionate effects are caused by how the policy affects credit conditions over time, leading to a switch to the lower regime, where monetary policy has the expected effects on economic activity and inflation.

Figure 7 compares dynamic responses to easing and tightening policies using large shocks across all horizons up to 48 months and both instruments. For the GK instrument, it is clear that responses of the short-rate and the credit spread are more persistent after a tightening policy. For both instruments, the response of prices to a tightening policy is more persistent, leading to considerable effects even at longer horizons. As discussed earlier, a policy easing leads to positive impact effects on economic activity if using the MAR instrument but negative effects if using the GK instrument. The estimated dynamic effects are such that there is evidence of long-run positive effects on activity following large shocks using both instruments. At short and medium horizons, positive effects following a policy easing are only observed using the MAR instrument.

To support these empirical results, we present in Table 4 68% confidence bands computed for $ASY^{+-(reg)}_{h=24,mp}$ and $ASY^{sl(reg)}_{h=24,mp}$ for both regimes and instruments. These confidence bands are useful to assess whether the evidence of sign and size asymmetries described earlier are statistically different from zero when taking into account parameter uncertainty on the computation of the responses. We compute bands for $ASY^{+-(reg)}_{h=24,mp}$ using both small (1 std) and large (4 std) shocks. Moreover, the bands for $ASY^{sl(reg)}_{h=24,mp}$ are computed for both tightening and easing shocks.

Table 4 results confirm that an easing shock has smaller effects on economic activity if credit conditions are tight at the time of the impact of shock, providing support for the relevance of the state of the economy on the findings reported by Barnichon and Matthes (2018). The results also show the importance of the responsiveness of the credit factor to monetary policy on findings of asymmetries from the size of the shock as Table 4 reveals that we are more likely to find statistically significant evidence of asymmetries using the GK instead of the MAR instrument. The results in the Table also reaffirm that a sharp decline in the short-rate due to monetary policy easing leads to disproportionally large effects on economic growth if the policy is implemented during periods of tight credit conditions, usually associated with recessions as indicated in Figure 2. The $ASY^{+-(reg)}_{h=24,mp}$ bands for large shocks in Table 4 suggest that the effect of expansionary policy on prices are stronger than the equivalent contractionary policy, if the policy is executed during the lower regime. The application of the ST-MAI model provides then additional context to the asymmetry evidence in Barnichon and Matthes (2018), by indicating that the asymmetric effects on prices are related to large policy changes during the regime of favorable credit markets.

In summary, as monetary policy shocks affect credit conditions, the ST-MAI model using the credit factor as transition variable can detect asymmetric effects due to the sign and size of monetary policy interventions. This novel evidence supports decisive monetary policy easing during periods of weak credit conditions, due to their expected significant positive effects on activity and prices.

3.7 Dynamic Responses for Key Variables

Our analysis has focused so far on the responses of the factors since they help us to be agnostic about the measurement of economic variables. In this section, we present responses for a small set of the endogenous variables included in the VAR as described in Table 1. These responses are computed as described in section 2.2 using the same $J = 400$ equally-spaced values from the saved posterior distribution of the ST-MAI parameters employed in the earlier Tables and Figures.

Figures 8 and 9 present responses of industrial production, unemployment, PCE and BAA spread to tightening and easing shocks identified using the MAR instrument. The choice of variables is as in Caldara and Herbst (2019). Figure 8 shows results for small shocks and Figure 9 for large shocks. Tightening and easing policy shocks have symmetric effects during the lower regime. Monetary policy tightening leads to a decline in industrial production, an increase in unemployment, a decrease in PCE and an increase in BAA spread during the lower regime. During the upper regime, monetary policy tightening has counter-intuitive and not significantly different from zero effects in industrial production and unemployment. For a sizeable easing policy change, instead, we find small effects on unemployment and mainly positive effects on industrial production. Responses of PCE differ across regimes as more substantial effects at short horizons are observed if the shock hits during the upper regime. It is also clear that substantial tightening shocks have less persistent effects than similar-sized easing shocks. Responses of the BAA spread are shaped differently from the ones computed for the credit factor, particularly during the upper regime. The BAA response in Figures 8 and 9 for the upper regime has a U-shape over the first year instead of the fast decay of the credit factor responses in Figure 7.

Based on Figures 8 and 9, we can claim that the dynamic transmission of monetary policy shocks to economic activity variables, such as industrial production and unemployment, and prices, such as PCE, may change. These asymmetries depend on the credit conditions regime at the time of the shock (state) and also on the sign (positive/negative) and size (small/large) of the shock.

3.8 Robustness to Histories Period

The impact effects of monetary policy shocks are estimated for a shorter sample period (1991-2012) than the one employed for the estimation of the ST-MAI (1982-2016) because of the data availability of the proxy variables. This choice is supported by the claim that we need a long time series to estimate changes in regime dynamics. The responses computed previously employed all histories over the 1982-2016 period. We check robustness by considering only histories during the 1991-2012 period when computing the dynamic effects of one-standard-deviation monetary policy tightening. This exercise is useful to see if the 80's observations lead to the empirical results discussed earlier.

The results we obtain (available on request) suggest that the responses are virtually the same. As a consequence, we can say that our results are robust to the choice of the period to set the lower and upper regime histories in the computation of the dynamic responses.

4 Conclusions

This paper improves our understanding of the dynamic links between credit conditions, monetary policy, and the macroeconomy. We do so by using a novel nonlinear VAR specification: a smooth transition multivariate autoregressive index (ST-MAI) model. In the ST-MAI model, the dynamic transmission of shocks to the endogenous variables are modelled as a function of a small number of observable factors, and their lags. These estimated factors allow us to be agnostic on the measurement of critical economic variables such as economic activity, prices, short-rate and credit conditions when performing structural analysis. They also allow us to use the information of a large number of economic and financial variables to estimate the nonlinear dynamic responses to monetary policy shocks.

By applying the ST-MAI model to US macroeconomic and financial data, we are able to provide the following new evidence. First, changes in the dynamic linkages between macroeconomic and financial variables are well-characterised by recurrent regime changes led by credit conditions. Second, because the probability of regime changes depends on credit conditions, the dynamic transmission of monetary policy shocks to credit conditions affects the likelihood of regime changes. This nonlinearity explains why we find evidence that monetary policy easing has effects on economic activity and prices that are not symmetric to monetary policy tightening. Third, the contemporaneous responsiveness of the credit spreads to monetary policy is critical when describing nonlinear dynamic effects, as different external instruments for monetary policy lead to different levels of responsiveness and asymmetric effects. Finally, the duration of the financial fragility episodes depends on the type of monetary policy carried out during the period. A resolute easing of monetary conditions increases the probability of moving out of the weak credit conditions regime, leading to disproportionate (in comparison to tightening) positive effects on economic activity and inflation.

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A Detailed Algorithm to Compute Responses

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

1. Draw a set of parameters – $A^{(j)} = (a_0^{(j)}, A_1^{(j)}, .., A_p^{(j)}, d_0^{(j)}, D_1^{(j)}, .., D_p^{(j)}), B_0^{(j)}, \Sigma_1^{(j)}, \Sigma_2^{(j)} \gamma^{(j)}, c^{(j)}$– from saved posterior distribution draws.

2. Using the transition function $\psi_t(\gamma^{(j)}, c^{(j)}, g_{t-1}^{(r,j)})$, define the set of regime 1 and regime 2 histories ($I_t^{(reg1)}$ and $I_t^{(reg2)}$).

3. Using the $A^{(j)}, B_0^{(j)}, \Sigma^{(j)}, \gamma^{(j)}, c^{(j)}$ and the set of histories from regime 1, compute two set of K paths conditional at each regime 1 history. These paths are the one conditional on the impact effect $\varpi_{(reg=1)}^{(r)}$ $Y_{t+2|t,\varpi_{(reg=1)}^{(r)}}^{(k)}, ..., Y_{t+h|t,\varpi_{(reg=1)}^{(r)}}^{(k)}$ and the one without it $Y_{t+2|t}^{(k)}, ..., Y_{t+h|t}^{(k)}$ for $k = 1, ..., K$, where K is the number of replications to approximate the conditional means. These paths are obtained by simulating the system using draws from $\varepsilon_{t+h}^{(k)} \sim N(0, \Sigma_{t+h|t}^{(k)})$, and as shocks affect $\psi_{t+h}(\gamma^{(j)}, c^{(j)}, g_{t+h-1}^{(r,j)})$, we simulate paths

also for $\Sigma^{(k)}_{t+1|t,\varpi^{(r)}_{(reg=1)}},...,\Sigma^{(k)}_{t+h|t,\varpi^{(r)}_{(reg=1)}}$ and $\Sigma^{(k)}_{t+1|t},...,\Sigma^{(k)}_{t+h|t}$. Responses for each history are computed by taking the differences between the average paths (with and without the shock), and regime 1 responses are then 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 $\varpi^{(r)}_{(reg=2)}$ as impact effect for each regime 2 history. Then compute regime 2 responses using the average response over all regime 2 histories.

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

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