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, where a small set of common shocks drive the dynamics of a large set of endogenous variables. We develop a Bayesian framework to estimate dynamic responses to structural shocks using the proposed nonlinear vector autoregressive model. We identify monetary policy shocks with the aid of high-frequency external instruments, and find significant differences in the responses across regimes, which are linked to credit conditions. As the transmission of shocks affects the probability of regime changes, the responses of economic activity and prices to monetary policy tightening/easing and large/small shocks are asymmetric.

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

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, 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, 2017). In this paper, we evaluate how the impact and the transmission of monetary policy shocks depend on financial conditions. Caldara and Herbst (2019) show the importance of allowing monetary policy to have a contemporaneous effect on credit spreads to establish the dynamic effects of monetary policy into the macroeconomy. 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) argue that the proxy can be improved by removing 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, 2017). The main advantage of smooth transition models is that at each point in time, the dynamic transmission is obtained by weighting upper and lower regime parameters, implying that the dynamic changes from the lower to the upper regime are smooth instead of abrupt as in Threshold and Markov-Switching models. Another advantage is that a combination of observed variables leads to regime changes, with a clear identification of the forces behind the switching. This is in contrast with the nonlinear projection approach in Barnichon and Matthes (2018) that uses the sign of past structural shocks to describe changes in the shock transmission. Smooth transition models nest threshold models, including the one employed by Balke (2000) to evaluate the impact of short-term credit risk as a nonlinear propagator of shocks. We estimate a smooth transition vector autoregressive model that uses a combination of monthly measures of credit conditions as a driver of time variation in the macro-financial linkages.

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 check whether the inclusion of a large information set in the estimation affects the estimated 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. As a consequence, we are agnostic about how to measure key economic variables such as economic activity, prices, the short-rate and 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 larger set of endogenous variables. So even if we include more than one policy-related endogenous variable, say use both the policy rate and the one-year rate, we will have only one common monetary policy shock, based on the MAI factor representation. By using the information of the reduced-form common monetary policy shock and the monetary policy proxy, we are then able to measure the impact of monetary shocks on all endogenous VAR 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 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. As we model regime changes as a function of observables, the probability of moving out from the current regime may change as response to shocks. The model help us to provide evidence of asymmetric effects from easing relative to tightening of monetary policy as in Barnichon and Matthes (2018). The advantage of our approach is that we are able to explain these effects by how the policies affect differently the probability of moving out of the regime

[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.

at the time of the shock.

We develop Metropolis-in-Gibbs algorithms to estimate the smooth transition MAI (ST-MAI) model. In contrast with factor-augmented VAR specifications as in Galvao and Owyang (2017), 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 (2017) to draw the parameters of the 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. The parameters of the transition function that define the timing of the regimes are estimated (in contrast to Aikman, Lehner, Liang and Modugno (2017)). We find evidence (based on a measure of fit) that the credit factor is the main trigger of regime changes, and that specifications with credit factor loadings normalized to the commercial paper spread values fit better.

The empirical results suggest important asymmetries related both to credit conditions and to the size and sign of the monetary shocks, identified with proxy measures. In particular, decisive monetary policy easing during a period of weak credit conditions can lead to beneficial effects in terms of economic activity and inflation, as the policy change leads to improvements in credit conditions and to a switch to the lower regime where monetary policy has the expected effects on economic activity and inflation. This novel empirical evidence, resulting from our large nonlinear model, highlights how monetary policy can be key 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 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:

$$Y_t = c_0 + \sum_{u=1}^{p} A_u B_0 Y_{t-u} + \varepsilon_t, \tag{2}$$

or

$$Y_t = c_0 + \sum_{u=1}^{p} A_u F_{t-u} + \varepsilon_t, \tag{3}$$

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 all the variables. 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 time variation in the parameters even when N is large.

Assume now that the parameters $c_0, A_1, ..., A_p$ change smoothly with the regime. Hence, a smooth transition MAI model (ST-MAI) is:

$$Y_t = c_0 + d_0\psi_t(\gamma, c, x_{t-1}) + \sum_{u=1}^{p} A_u F_{t-u} + \sum_{u=1}^{p} \psi_t(\gamma, c, x_{t-1}) D_u F_{t-u} + \varepsilon_t, \quad (5)$$

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 important feature of macroeconomic regime changes as suggested by the empirical applications surveyed 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:

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

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

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

the (macroeconomic) model dynamics. We use single factors for computational simplicity and also to determine empirically which is the key driver of regime changes.[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 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 even if only $g_{t-1}^{(r)}$ drives regime changes. The advantage of this approach is that the interpretation of the empirical results is easier if we know what is driving regime changes, while a filtering step is not required as part of 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 Carriero, Clark and Marcellino (2016) 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 also allow for covariance changes over regimes. This may have important consequences for computation of responses to structural (common) shocks.

[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.

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. This implies that 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 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 that 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, being mainly spread variables. One of them is the excess bond premium computed using corporate bond yields by Gilchrist and Zakrajsek (2012). The remaining five spread measures have been considered by Hatzius, Hooper, Mishkin, Schoenholtz and Watson (2010) and are also part of financial stress indices periodically released by regional Feds (Chicago, St.

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

Louis and Cleveland). The set of spreads includes the 3-month commercial paper spread over the 3-month Treasury bill, which was employed as 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, Kapetanios and Marcellino (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 we are considering 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:

$$F_t = B_0(c_0 + d_0\psi_t(\gamma, c, x_{t-1})) + B_0\sum_{u=1}^{p} A_u F_{t-u} + B_0\sum_{u=1}^{p}\psi_t(\gamma, c, x_{t-1})D_u F_{t-u} + u_t, \quad (9)$$

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 dynamics of the N observables in the system.

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

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

poraneous 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 $H^{(r=mp)}_{(reg)}$ for $reg = 1, 2$ following the approach in Gertler and Karadi (2015). This implies that we employ $u^{(mp)}_t$ 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 $u^{(mp)}_t$. We estimate the regression coefficients using the full sample available for the instrument as in Gertler and Karadi (2015). A final step to obtain $H^{(mp)}_{(reg)}$ 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 $H^{(mp)}_{(reg)}$ 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 $H^{(r=mp)}_{(reg)}$ 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 longer time period, which better enables to capture regime changes.

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 ξ_t, we find no evidence of serial correlation in u_t. This helps to support the assumption of exogeneity of the proxy with respect to the other non-identified structural shocks.

Our ultimate interest, however, is to measure the impact effect of the structural common shocks 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, Kapetanios and Marcellino (2016)). The idiosyncratic shocks are orthogonal to the common shocks because, as $u_t = B_0\varepsilon_t$ and $\xi_t = B_{0\perp}\Sigma_t^{-1}\varepsilon_t$, we have $E[u_t\xi_t'] = B_0\varepsilon_t\varepsilon_t'\Sigma_t^{-1}B_{0\perp}' = 0$. 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 main 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 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:

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

For the following horizons, we compute responses as:

$$IR_{t,h,r} = \frac{\partial Y_{t+h|t}}{\partial v_{t+1}^{(r)}} = E[Y_{t+h}|I_t, \varpi_{(reg)}^{(r)}] - E[Y_{t+h}|I_t] \quad (12)$$

$$\text{for } h = 2, ..., H \text{ and for } t \,\epsilon\, reg,\ reg = 1, 2,$$

where $I_t = (Y'_t, .., Y'_{t-p+1})'$. This suggests that responses are computed by comparing the paths of the endogenous variables over h horizons under two scenarios: a shock has hit with effect $\varpi^{(r)}_{(reg)}$ at $h = 1$ and no exogenous shocks have affected the endogenous variables path.

In both cases, K paths for Y_{t+h} are simulated assuming as initial values I_t and using the parameters of the ST-MAI system in eq. (5) and eq. (8). These simulated paths are obtained using draws from $\varepsilon^{(k)}_{t+h} \sim N(0, \Sigma^{(k)}_{t+h})$ for $h = 2, ..., H$ where $k = 1, ..., K$.[6] The variance-covariance matrix $\Sigma^{(k)}_{t+h}$ 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 using:

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

An implication of equation (12) is that we have one response function over horizons $h = 2, ..., H$ 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:

$$IR^{reg1}_{h,r} = 1/T_1 \sum_{t=1}^{T_1} IR^{(reg1)}_{t,h,r} \qquad (13)$$

$$IR^{reg2}_{h,r} = 1/T_2 \sum_{t=1}^{T_2} IR^{(reg2)}_{t,h,r} \qquad (14)$$

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

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

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

[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 both thresholds are set to 0.5.

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 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, and the size of the shock affects proportionally the dynamic responses. 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 $H_{(reg)}^{(r=mp)}$ 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:

$$IR_{t,h=1,r(neg)} = \Sigma_{reg} B_0' \Omega_{reg}^{-1} (-H_{(reg)}^{(r)}) = \varpi_{(reg)}^{(r,neg)} \ .$$

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

$$IR_{t,h=1,r(\varkappa)} = \Sigma_{reg} B_0' \Omega_{reg}^{-1} (\varkappa H_{(reg)}^{(r)}) = \varpi_{(reg)}^{(r,\varkappa)},$$

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:

$$ASY_{h,r,t}^{+-} = IR_{t,h,r(pos)} + IR_{t,h,r(neg)}.$$

[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.

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

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

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 $ASY_{h,r}^{+-(reg1)}$ or $ASY_{h,r}^{+-(reg2)}$ are nonzero.

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

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

If large shocks have different effects from small shocks in, say, regime 2, we expect that $ASY_{h,r}^{ls(reg2)}$ 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, Kapetanios and Marcellino (2016). Following Carriero, Kapetanios and Marcellino (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:

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

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 (2017). 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 (2017). 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, Clark and Marcellino (2016). 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, Kapetanios and Marcellino (2016). This step has a tuning parameter Δ_b calibrated to achieve rejection rates of around 70%. This random-walk step employs proposal distribution variances based on factors estimated by principal component over a pre-sample period.

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 employed in the estimation of the factor loadings B_0. Availability over a more extended period at the monthly frequency was one of the criteria to select variables to measure activity, inflation, monetary policy and credit conditions. This excludes most of the measures of supply of credit, but leads 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). Variables are transformed as indicated in Table 1 and the ST-MAI parameters are estimated to their normalized values. The structural VAR literature to measure the effects of monetary policy shocks typically employs activity and price variables in log-levels instead of monthly differences as indicated in Table 1. Because it is unlikely that the regime changes affect how the variables move together in the long-run (cointegration among variables) and we need stationary variables to lead to regime changes, we prefer to estimate the ST-MAI model with activity and prices variables in first differences. We then compute cumulated responses for all activity and price variables to be comparable with the results in the literature .

We set the priors' hyperparameters 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. 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 transition variable, and the commercial paper spread as the variable with normalized loading 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 also 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 and median of the likelihood values, including the 16% and 84% percentiles.

We also consider the following alternative specifications. A specification with three factors instead of four where the two short-term rate variables 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 support for our choice of the ST-MAI baseline. Specifically, using a year-on-year transformation of the credit factor $g_t^{(4)}$ as transition variable, we consider the effects of the loadings normalization in (the over-identified) B_0. Table 2 shows the likelihood for specifications where the normalization is applied to each one of the observables in the credit factor. The normalization changes the scale of the estimated factor and may have an impact on the estimation of the loadings in B_0 and of the smooth transition parameters γ and c, even if the hyper-parameters are kept fixed as described above. It is clear that the normalization applied to commercial paper spread delivers the best fit, and avoids convergence issues (which emerge for example with the TED spread). Table 2 also shows results of ST-MAI models that use the activity factor as transition variable. This alternative choice again deteriorates fit.

3.2 Factor Identification

Using the baseline ST-MAI specification, we compute the posterior median of the annualized factors over the estimation period (1982M3-2016M6). 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 a 86% correlation with the Philadelphia Fed activity index, and the credit factor has a 80% correlation with the Chicago Fed Financial Condition Index. The correlation between the short-rate factor and Financial Condition index is clearly smaller at 45%.

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 80's monthly periods. Then the regime is identified again in the build up to the 2001 and the 2008/9 recessions.

Figure 1B 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 clearly observe that there are many data points between 0 and 1, indicating that a smooth transition from the lower to the upper regime is well supported by the data. The Figure also indicates a larger 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 (2017), but to called as a regime with weaker credit conditions.[9]

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

[9]Some of the alternative ST-MAI specifications considered in Table 1 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 1 support the baseline specification.

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) monetary policy 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 low variability periods identified for the proxy 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 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 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 and reduced-form shocks.

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 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 evaluating the effect of monetary policy shocks using responses computed for factors is that we take into consideration measurement issues, that is, there are many observed monthly measures for the four key economic variables (economic activity, inflation, short rate and credit spreads). We analyze responses for individual variables in section 3.7.

Figures 4 and 5 present median responses and the 18% and 84% quantiles to an one-standard deviation monetary policy tightening. We present responses for horizons up to 48 months and for each set of histories (lower and upper regimes). Figure 4 presents responses with the impact effects of monetary policy 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 in each 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 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 result of a policy tightening. Median responses of credit to the monetary policy tightening at impact using the GK instrument are about 12 basis point 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 lower regime because of the estimated regime changes in the variance-covariance matrix of reduced-form shocks. Even more notable are 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. Negative effects on prices are larger 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. The reversal effect is smaller using the GK proxy, but then impact effects are significantly positive at short horizons, leading to counter-intuitive results: monetary policy tightening improves economic activity. Two comments apply. First, confidence bands are wide and include zero for most of the horizons, so one could claim no significant effects in economic activity in the upper regime. Second, the issue of counter-intuitive effects of monetary policy at short horizons and at some points in time 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 an expansionary monetary policy shock has weaker effect on unemployment than contractionary shocks, and that the same shock has stronger effects on inflation. They propose a methodology that approximates nonlinearities in the responses to monetary policy shocks for positive and negative shocks in a way that resembles how we deal with regime changes. The mechanism that may lead to monetary policy tightening and easing to have different effects using the ST-MAI model is linked to the fact the monetary policy changes affect the probability of regime changes.

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 an one-standard deviation shock. If the shock hits the system in the lower regime, a tightening shock as the one displayed in Figures 4 and 5 leads to 7-8% probability of switching to the upper regime (depends on the instrument), but an easing shock of similar size (using $-H_{(reg)}^{(mp)}$ instead of $H_{(reg)}^{(mp)}$ 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 after a tightening shock is between 79 and 82% but following a easing is between 67% and 71%.

Because the variable that leads to regime change is linked to the credit spread factor, the probability of being in the upper regime after monetary policy tightening is larger using the GK instrument, since the use of the GK proxy leads to a larger estimated responsiveness of credit to monetary policy. Similar effects explain why the probability of being in the upper regime following an easing policy is in general larger 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 find that expansionary shocks lead to flatter effects on economic activity (the reversal effect after one year is not as strong) and stronger effects on prices (effects are more persistent). The advantage of the application of ST-MAI model instead of the approach in Barnichon and Matthes (2018) is that we are able to provide a reasoning for these asymmetric effects: tightening and easing the policy rate have opposite effects on credit conditions which have nonlinear effects on the transmission of the shocks. As consequence, we are able to link the asymmetry evidence in Caldara and Herbst (2019) with the evidence on the importance of credit conditions to business cycle in Lopez-Salido et al. (2017).

Another important aspect of our empirical approach is that we are agnostic on the best way to measure credit conditions by using six different credit spread measures. We are also agnostic on the measurement of activity, prices and the short-rate by considering both the policy rate and the one-year rate.

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 estimate of the response after 24 months of each factor to either a tightening or a easing shock hitting either in the lower or the upper regime for both GK and MAR instruments. Table 3A provides responses for one-standard deviation shocks (as in Figures 4, 5 and 6) and in Table 3B, we display responses for four-standard deviation shocks. The four-standard deviation shock is computed by using $4H^{(mp)}_{(reg)}$ instead of $H^{(mp)}_{(reg)}$ as described in section 2.2.2. For the upper regime, the effect on the short rate is on average about 100 basis points at the impact, 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 effects equal to easing effects in absolute values. It is clear 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 changing 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. Sign asymmetries are even larger for shocks hitting during the upper regime. During the upper regime, tightening 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 4 times the values in Table 3A. As in the case of the sign of the shock, a large shock may lead to a larger probability of regime change leading to nonlinear effects in the transmission of shocks. A large easing shock increases the probability of switching out of the weak credit conditions, the 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. Inflation accelerates faster, as economic activity also reacts positively at the 24 months horizon.

These empirical results suggest that decisive monetary policy easing during the period of weak credit conditions can lead to beneficial effects in terms of economic activity, as the policy change leads to improvements in credit conditions and to a regime change 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 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 large 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 dynamic effects are such that following large shocks we find evidence of long-run positive effects on activity 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 68% confidence bands computed for $ASY_{h=24,mp}^{+-(reg)}$ and $ASY_{h=24,mp}^{sl(reg)}$ for both regimes and instruments in Table 4. These confidence bands are useful to assess whether the evidence of sign and size asymmetries described earlier are statistically not zero when taking in to account the effects of parameter uncertainty on the computation of the responses. We compute bands for $ASY_{h=24,mp}^{+-(reg)}$ using both small (1 std) and large (4 std; appr. 100 basis point on short-rate in the upper regime) shocks. And the bands for $ASY_{h=24,mp}^{sl(reg)}$ 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 confirm that a sharp decline in the short rate due to monetary policy easing leads to disproportionally large effects on economic growth if policy is implemented during periods of tight credit conditions, usually associated with recessions as indicated in Figure 2. The $ASY_{h=24,mp}^{+-(reg)}$ bands for large shocks provide evidence that expansionary policy effects on prices are stronger that the equivalent sized contractionary policy if the policy change is performed 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 favourable credit markets.

In summary, as monetary policy affects credit conditions, the ST-MAI model using the credit factor as transition variable is able to detect asymmetric effects due to 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 large 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 productions, 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 large easing policy change, instead, we find small effects on unemployment, and mainly positive effects on industrial production. Responses of PCE differ across regimes as increasing effects at short horizons are observed only if the shock hits during the upper regime. It is also clear that large tightening shocks have less persistent effects than large 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.

Figures 8 and 9 support our results indicating that dynamic transmission of monetary policy shocks to economic activity variables, such as industrial production and unemployment, and prices, such as PCE, may change depending on the credit conditions at 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 using the proxy 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). 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 is useful to see if our results are led by the 1980's observations. Our results (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 time period to set the lower and upper regime histories in the computation of the dynamic responses.

4 Conclusions

This paper sheds additional light on the relationship between credit conditions and the macroeconomy, using a novel large 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. The advantage of our estimated factors is that they allow us to be agnostic about the measuring of key economic variables such as economic activity, prices, short-rate and credit conditions when performing structural analysis. The ST-MAI model combines information of a set of related observed time series to measure each one of these variables.

Empirically, statistical evidence supports the credit factor as the preferred transition variable, the trigger of parameter changes, with a history for the endogenously identified periods of tight credit conditions that includes recession periods. Hence, credit conditions, as measured by a combination of various credit spread indicators, can alter the dynamic relationships among economic variables. Moreover, during periods of tight credit conditions, the effects of monetary shocks, identified using alternative high-frequency proxies, can be quite different from those of favourable credit conditions. Asymmetries across regimes are a consequence of the ST-MAI model regime-dependent dynamic coefficients estimates. Because the probability of regime changes depends on current 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. The estimated dynamic transmissions of activity and prices also indicate that effects of large monetary policy shocks are not proportional to small shocks.

Our empirical results suggest that the duration of the financial fragility episodes depends on the type of monetary policy carried out during the period. Decisive monetary policy easing during a period of weak credit conditions can lead to beneficial effects in terms of economic activity and inflation, as the policy change leads to improvements in credit conditions and to a switch to the lower regime where monetary policy has the expected 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 – $A^{(j)} = (A_1^{(j)}, .., A_p^{(j)}, D_1^{(j)}, .., D_p^{(j)}), B_0^{(j)}, \Sigma_1^{(j)}, \Sigma_2^{(j)} \gamma^{(j)}, c^{(j)}$– from saved posterior distribution draws.

2. Using the transition function $\Pi_t(\gamma^{(j)}, c^{(j)}, x_{t-1}^{(j)})$, 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 a set of K paths with and without the impact of $v_1^{(r)}$ for each history $t = 1, ..., T_1$. These paths are $Y^{(k)}_{t+1|v_1^{(r)}}, ..., Y^{(k)}_{t+h|v_1^{(r)}}$ and $Y^{(k)}_{t+1}, ..., Y^{(k)}_{t+h}$ for $k = 1, ..., K$, where K is the number of replications to approximate the conditional means. Based on the average over the K paths, we obtain $\widehat{Y}_{t+1|v_1^{(r)}}, ..., \widehat{Y}_{t+h|v_1^{(r)}}$ and $\widehat{Y}_{t+1}, ..., \widehat{Y}_{t+h}$ for each set of histories. These paths are obtained by simulating the system using draws from $\varepsilon^{(k)}_{t+h} \sim N(0, \Sigma^{(k)}_{t+h|t})$. This implies that we simulate paths also for $\Sigma^{(k)}_{t+1|v_1^{(r)}}, ..., \Sigma^{(k)}_{t+h|v_1^{(r)}}$ 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 $t = 1, ..., T_2$. Compute then the regime 2 responses by taking the differences between the average paths (with and without the shock) for each history, and then computing the average response over all regime 1 histories.

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

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