The Interaction of Fiscal and Monetary Policy Shocks: A Time Varying Parameters FAVAR Approach *

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Abstract

This paper analyses the effects of the interaction of fiscal and monetary policy shocks on macroeconomic and financial variables using a FAVAR model with time varying parameters (TVP FAVAR). With respect to traditional VARs, this methodology increases the information set and permits the impulse response analysis for a large number of variables. In particular, thanks to the time varying structure of the model we assess the impact of a monetary policy shock combined with a fiscal policy shock identified via the narrative approach. This procedure allows to study the complementarity of macroeconomic measures and provides new insights in the transmission mechanism of fiscal and monetary policy. The impulse response function shows that the impact of a monetary policy shock is sensitive to the fiscal regime and sheds some light on the reaction of financial markets to different policy mix.

Keywords: FAVAR, time varying parameters, fiscal and monetary policy

JEL classification: E63, E65, C32

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1 Introduction

After the recent financial crisis and the Great Recession the effectiveness of macroeconomic policies to sustain the economic recovery has been largely discussed by economists and policy makers. Among others, two issues are debated: how do financial markets react to policy changes and how do fiscal and monetary policies interact. The financial turmoil after the collapse of Lehman Brother and the following credit crunch have shown the importance of financial markets in the amplification and propagation of a financial shock into the real economy. For this reason, theoretical macroeconomic models started to incorporate the banking sector and the financial markets for their policy analysis. In addition, when Central Banks of industrial countries cut the interest rates to low levels and the monetary policy became ineffective to stimulate the economy, fiscal authorities stepped in with fiscal packages to foster the economic growth. An intense debate among scholars has followed about the effect of fiscal policy when monetary policy is constrained by the zero lower bound.

The objective of this paper is to analyse how macroeconomic and financial variables react to a combination of fiscal and monetary policy shocks. We estimate the impulse response of a monetary policy shock under different monetary policy regimes and the impulse response of a fiscal policy shock under different monetary policy regimes. In particular, we focus on the reaction of financial variables that played a key role in the contagion of the liquidity crisis in 2007-2008. Macroeconometric models usually estimate the consequences of a policy shock regardless of the implementation of other policies. Christiano et al. (2011) simulate the impact of a government spending shock when the zero lower bound is binding in a dynamic stochastic general equilibrium model. They argue that they cannot extend the analysis employing structural VARs models, because it may be misleading to compare results in countries where the monetary policy is constrained by the zero lower bound and in countries where the monetary policy is not constrained. Ilzetzki et al. (2011) using a panel VAR assess the impact of a fiscal policy shock under different exchange rate regimes, distinguishing between economies with a flexible exchange rate regime and economies with a fixed exchange rate regime.

In this paper we adopt a different strategy to study the complementarity of fiscal and monetary policy. We use external information to identify fiscal (monetary) policy shock from episodes of large and exogenous variation of fiscal (monetary) variables and at the same time we simulate a monetary (fiscal) shock from a Time Varying Parameters Factor Augmented VAR (TVP FAVAR) model, which combines the FAVAR approach and the Time-varying parameter approach. The TVP FAVAR model is more suitable than a traditional VAR to trace out the effect of monetary and fiscal innovations for several reasons. The first one is that VARs can contain only a small number of variables to conserve degrees of freedom. The small information set in these models can lead to problems of information insufficiency, because the variables considered do not convey all of the relevant information about the economy considered by agents and policymakers (see Fernandez-Villaverde et al. (2007) and Forni and Gambetti (2011)). Moreover, from a practical perspective the impulse response analysis can be carried out only for the few variables included in the VARs. So they are unable to provide inference on a large number of variables that may be of interest to policy makers. For these reasons, the FAVAR approach is particular appealing since it incorporates a huge number of information in a parsimonious way, by including few factors that summarize hundreds of additional variables and which capture the fundamental economic forces. Bernanke and Boivin (2003) show that the use of factors can improve the estimation of Fed's policy reaction function. Bernanke et al. (2005) find that price and liquidity puzzles present in structural VARs disappear when factors are included, suggesting that a FAVAR model is successful in capturing relevant additional information missing from VARs.

However, FAVAR models with time invarying parameters abstract from the possibility of changes in the policy transmission mechanism and the way the exogenous shocks change over time. Perotti (2005) and Bilbiie et al. (2008) show that the transmission mechanism of fiscal policy changed after 1980 because of the modification in the conduct of monetary policy and the consequence of the increase in asset market participation on private consumption. Similarly, Boivin and Giannoni (2006) find that domestic transmission of monetary policy has changed over time. So in this paper we model time variations in coefficients and in the variance covariance matrix to consider structural changes, instead of estimate the impulse response function of VARs for different subsamples. Moreover, time variation is a crucial element to assess the interaction of monetary and fiscal policy. This is because the impulse responses of monetary (fiscal) shocks are estimated when the economy is struck by a fiscal (monetary) shock, identified using the narrative approach. In other words, we identify a policy shock occurred in the US economy and in the same period we simulate the effect of an additional policy shock. Hence, we can compare the impulse response function under different policy regimes. In this way we mix the structural VAR (SVAR) approach and the narrative approach, using three sources. First, Romer and Romer (1989) for episodes of exogenous monetary policy shocks. Second, the narrative records of Romer and Romer (2010) for exogenous tax increases to reduce the public deficit and tax reductions to foster long-term growth. Third, the military dates considered Ramey and Shapiro (1998) for exogenous expansions in public spending.

Del Negro and Otreck (2008) is the first paper that combines dynamic factor models and parameter instability in order to capture changes in international business cycle. In their study factors are the means to identify international forces driving business cycles and they interpret a variation in the factor volatility as a change in the importance of global and regional shocks. The factor structure is used to extract comovements at global and regional levels. Moreover, in their specification factor loadings are time varying to allow the sensitivity of each country to global shocks to evolve over time because of changes in policy or in the structure of the economy. Liu et al. (2011) use a TVP FAVAR model to analyze the international transmission of money supply, demand and supply shocks. They include factors for foreign real activity, foreign inflation and foreign interest rates extracted from separated blocks of data for each variable considered. Their model allows for time variation in factor loadings and in the variance covariance matrix. Korobilis (2009) and Eickmeier et al. (2011) use a TVP FAVAR model to analyze how the transmission of monetary policy evolved over time.

The remainder of this paper is organized as follows: Section 2 introduces the TVP FAVAR and explain the estimation; Section 3 discusses the identification of fiscal and monetary policy shocks; Section 4 shows the empirical results and Section 5 concludes.

2 Methodology

2.1 The Model

The starting point is a standard VAR model. Let Y_t denotes a vector of m observable variables, including the military buildup dummy variable, inflation, industrial production and the federal fund rate :

$$Y_t = A(L)Y_{t-1} + e_t \tag{1}$$

where A(L) is a vector polynomial in the lag operator and e_t is a vector of reduced form residuals. We combine the standard VAR model with a dynamic factor model to increase the information set and extend the impulse response analysis to additional variables. In particular, we add the following equation that links a large matrix X_t, consisting of n macroeoconomic and financial variables, with the m observable factors Y_t and few k unobservable common factors:

$$X_t = \Lambda^f F_t + \Lambda^y Y_t + u_t \tag{2}$$

Unobservable factors are assumed to be orthonormal and uncorrelated with the errors u_t. In addition, $E(u_t) = 0$ and $E(u_t u_t') = H_t$, where H_t is a diagonal matrix with elements $h_{i,t}$; Λ^f is a (n x k) matrix of time varying factor loadings relating F_t to X_t and Λ_t^y is a (n x m) matrix of time varying loadings relating Y_t to X_t; $\lambda_{i,t}$ are the elements of Λ^f and Λ^y. Unobservable factors F_t summarize the information set X_t and represent forces that affect economic variables included in X_t simultanously.

Finally, we allow the model for drifting coefficients and a multivariate stochastic volatility, obtaining the following equation :

$$FY_t = \Phi_{1,t} FY_{t-1} + ... + \Phi_{p,t} FY_{t-p} + v_t \tag{3}$$

where FY_t is the vector combining k unobservable and m observable factors; $\Phi_{i,t}, i = 1, ..., p$ are (m x m) matrices of coefficients; v_t is the vector of heteroscedastic unobservable shocks with variance covariance matrix Ω_t. So the initial VAR model is incremented with latent factors and time varying parameters. As in Cogley and Sargent (2005) and Primiceri (2005), the variance covariance matrix Ω_t is factored as:

$$A_t \Omega_t A_t' = \Sigma_t \Sigma_t' \tag{4}$$

or equivalently

$$\Omega_t = A_t^{-1} \Sigma_t \Sigma_t' (A_t')^{-1} \tag{5}$$

where A_t is a lower triangular matrix and Σ_t is a diagonal matrix:

$$A_t = \begin{bmatrix} 1 & 0 & \dots & 0 \\ \alpha_{21,t} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ \alpha_{n1,t} & \dots & \alpha_{nn,t} & 1 \end{bmatrix} \qquad \Sigma_t = \begin{bmatrix} \sigma_{1,t} & 0 & \dots & 0 \\ 0 & \sigma_{2,t} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \dots & 0 & \sigma_{n,t} \end{bmatrix}$$

Equation (3) can be written in a more compact way:

$$FY_t = Z_t' \Phi_t + A_t^{-1} \Sigma_t \epsilon_t \tag{6}$$

$$Z_t' = I_n \otimes [\tilde{Y}_{t-1}, ..., \tilde{Y}_{t-p}]$$

where $\epsilon_t \sim N(0, I_n)$ and $\otimes$ denotes the Kronecker product. Let α_t the vector of non-zero and non-one elements of matrix A_t and σ_t the vector of the diagonal elements of the matrix Σ_t. Parameters Φ_t and α_t evolve as driftless random walks and σ_t as geometric random walk: [1]

$$\Phi_t = \Phi_{t-1} + \eta_t^{\Phi} \quad , \quad \eta_t^{\Phi} \sim N(0, Q) \tag{7}$$

$$\alpha_t = \alpha_{t-1} + \eta_t^{\alpha} \quad , \quad \eta_t^{\alpha} \sim N(0, S) \tag{8}$$

$$log\sigma_t = log\sigma_{t-1} + \eta_t^{\sigma} \ , \quad \eta_t^{\sigma} \sim N(0, W) \tag{9}$$

where $\eta_t^{\theta}, \theta = \Phi, \alpha, \sigma$ are innovation vectors independent each other. Q, S, W are positive definite matrices and S is block diagonal with blocks corresponding to parameters belonging to separate equations. In other words, the coefficients of the contemporanous relations among variables are assumed to evolve independently in each eqution.

2.2 Estimation

The TVP FAVAR model can be represented in the following linear state-space form, where the measurement equation is the observation equation and the VAR equation is the state equation:

$$\begin{bmatrix} X_t \\ Y_t \end{bmatrix} = \begin{bmatrix} \Lambda_t^f & \Lambda_t^y \\ 0 & I \end{bmatrix} \begin{bmatrix} F_t \\ Y_t \end{bmatrix} + \begin{bmatrix} u_t \\ 0 \end{bmatrix} \tag{10}$$

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + A_t^{-1} \Sigma_t \epsilon_t \tag{11}$$

The model is estimated in two stages. The first stage involves estimating the unobserved factors F_t as first principal components of X_t in the measurement equation (10), obtaining $\hat{F}_t$. The second stage involves estimating the parameters of the TVP FAVAR model in the state equation (11) via Bayesian methods with F_t replaced by $\hat{F}_t$.

Forni et al. (2000) and Stock and Watson (2002) show that principal components are consistent estimators of the common factors for both the cross-sectional dimension n and the sample size T going to infinity for any path of n and T. The factors are estimated consistently even if there is some time variation in the loading parameters, as argued by Stock and Watson (2008) and Banjeree et al. (2008). Hence, principal components have been considered as the solution of a computational problem since they can be easily computed even if the cross-sectional dimension n is large. An alternative approach consists in estimating equation (10) and equation (11) simultanouly by Gaussian maximum likelihood or by Quasi maximum likelihood using the Kalman filter. Doz et al. (2011) show that maximum-likelihood estimates of the common factors are also consistent for n and T going to infinity along any path. To measure the effects of monetary policy Bernanke et al. (2005) estimate a FAVAR model using both the two-step principal components aproach and the single-step likelihood method and obtain essentially the same results. Liu et al.

[1] This is a common specification in time varying parameter models, see e.g. Nyblom (1989). Giordani and Kohn (2008), Koop at al. (2009) and Korobilis (2009) use the mixture innovation approach for the dynamics of parameters instead of normal innovations. in this case the random walk is augmented with a mixture innovation specfication and one component follows a 0/1 Markov process allowing the model to be time-varying at some points and contant at other ones. Another alternative consists in modeling time variation as the result of switching across regimes, asin Sims and Zha (2006), or as structural breaks as in Doyle and Faust (2005)

(2009) and Mumtaz and Surico (2011) follow the one-step strategy proposed by Bernanke et al. (2005) based on Gibbs sampling for the estimation of TVP FAVAR models. Instead, Korobilis (2009) and Eickmeier et al. (2011) estimate the factors as first principal components. In this study we follow the two-step approach as it requires weaker distributional assumptions of residuals and it is computationally less burdensome, considering the of high number of parameters.

Before estimating equation (10) identification restrictions are imposed to identify uniquely the factors and the associated loadings because of the indeterminancy of the model. Following Bernanke et al. (2005), factors are restricted by $F'F/T = I$, obtaining $\hat{F} = \sqrt{T}\hat{Z}$, where $\hat{Z}$ are the eigenvectors corresponding to the K largest eigenvalues of XX', sorted in descending order to deliver the common components $F\Lambda^{f'}$ and the factor space. The model is then estimated by simulating the distribution of the parameters of interest, given the data. We apply a Gibbs sampling algorithm with the conditional prior and posterior distributions described below.

Prior distributions and initial values

The choice of the prior distributions follows Bernanke et al. (2005) and Korobilis (2009) for the measurement equation (10) and Primiceri (2005) for the state equation (11). In the measurement equation (10) an uninformative prior distribution is used for the matrix of loadings $L_t = \begin{bmatrix} \Lambda_t^f & \Lambda_t^y \\ 0 & I \end{bmatrix}$ and the inverse gamma distribution for the diagonal elements of H_t:

$$L_0 \sim N(0\ ,\ 4I)$$

$$H_0 \sim iG(a_0\ ,\ b_0)$$

where $a_0 = 0.01$ and $b_0 = 0.01$ denote the scale parameter and the shape parameter respectively.

In the state equation (11) diffuse priors based on OLS estimations on the overall sample are used and initial states for all the parameters are independent. In particular, for Φ_t and A_t Normal priors are considered and the mean and variance are chosen to be OLS point estimates and four times its variance in a time invariant VAR. Elements of Σ_t are assumed to follow a log Normal distribution. The mean of the distribution is chosen to be logarithm of the OLS point estimates of the standard errors of the same time invariant VAR, while the variance covariance matrix is assumed to be the identity matrix. The priors for the hyperparameters Q_t, W_t and S_t are assumed to be distributed as independent inverse-Wishart. Summarizing, the priors in the state equation (11) take the forms:

$$\Phi_0 \sim N(\hat{\Phi}\ ,\ 4V(\hat{\Phi}))$$

$$A_0 \sim N(\hat{A}\ ,\ 4V(\hat{A}))$$

$$log\sigma_0 \sim N(log\hat{\sigma}\ ,\ I_n)$$

$$Q \sim iW(k_\Phi^2 \cdot (1 + n_\Phi) \cdot V(\hat{\Phi})\ ,\ 1 + n_\Phi)$$

$$S \sim iW(k_\alpha^2 \cdot (1+n_\alpha) \cdot V(\hat{I_n}) \ , \ 1+n_\alpha)$$

$$W \sim iW(k_\sigma^2 \cdot (1+n_\sigma) \cdot V(\hat{A}) \ , \ 1+n_\sigma)$$

where n_θ denotes the number of elements on each state vector $\theta = \Phi, \alpha, \sigma$; k_θ are tuning constant: $k_\Phi = 0.07; k_\alpha = 0.1; k_s = 0.01$.

Simulating the posterior distributions

The factor loadings in equation (10) are sampled from :

$$L_i \sim N(L^* \ , \ M^*) \text{ ; where } L^* = M^* + H_{i,i}^{-1} \cdot FY' \cdot X_{i,t} \text{ and } M^* = (4I + H_{i,i}^{-1} + FY' \cdot FY)^{-1}.$$

Since the errors are assumed uncorrelated and the variance covariance matrix is diagonal, OLS are applied equation by equation to obtain the matrix of factor loadings $\hat{\Lambda}$ and the residuals $\hat{\epsilon}$. The diagonal elements $H_{i,i}$ are drawn from the following inverse gamma distribution:

$$H_{i,i} \sim iG(\bar{H}_{i,i} \ , \ T + b_0) \text{ ; where } \bar{H}_{i,i} = \hat{\epsilon_i}'\hat{\epsilon_i} + a_0$$

For equation (11) a Gibbs sampling procedure is applied drawing sequentially time varying coefficients (Φ_t), simultaneous relations (A_t), volatilities (Σ_t) and hyperparameters (Q_t, W_t and S_t), conditional on observed and unobserved factors in FY_t and all other parameters. This amounts to reducing a complex problem into a sequence of tractable ones, sampling from conditional distributions for a subset of parameters conditional on all the other parameters. This Gibbs sampling procedure reduces to four main blocks. In the first block Φ_t is drawn conditional on FY_T, A_t, Σ_t and hyperparameters. In the second block A_t is drawn conditional on FY_T, Φ_t, Σ_t and hyperparameters. In the third block Σ_t is drawn conditional on FY_T, Φ_t, A_t, and hyperparameters. Finally, the hyperparameters Q_t,W_t and the diagonal blocks in S_t are drawn from inverse-Wishart posterior distributions independent each other conditional on and FY_t, Φ_t, A_t and Σ_t. [2] In the first three blocks we reduce the problem into three state space linear and gaussian forms and apply the Carter and Kohn (1994) algorithm.

The first step consists in drawig coefficient states Φ_t from the linear and gaussian state space form given by equations (6) and (7) using kalman filter and backward recursion. [3]

The second step consists in drawing the covariance states, considering equation (6) as the following:

$$A_t(FY_t - Z_t'\Phi_t) = A_t\hat{y_t} = \Sigma_t\epsilon_t \tag{12}$$

Since A_t is a lower triangular matrix with ones on the main diagonal, equation (12) can be written as

$$\hat{y_t} = \tilde{Z}_t\alpha_t + \Sigma_t\epsilon_t \tag{13}$$

where α_t is defined in equation (6). $\tilde{X}_t$ is the following matrix

[2] We use 20,000 replications in these Gibbs runs discarding the first 2,000 as burn-in.
[3] See the appendix B for a complete description of the algorithm.

$$\tilde{Z}_t = \begin{bmatrix} 0 & \dots & \dots & 0 \\ -\hat{y}_{1,t} & 0 & \ddots & 0 \\ 0 & -\hat{y}_{[1,2],t} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \dots & 0 & -\hat{y}_{[1,\dots,n-1],t} \end{bmatrix}$$

where $\hat{y}_{[1,\dots,i],t}$ denotes the row vector $[\hat{y}_{1,t}, \hat{y}_{2,t}, .., \hat{y}_{i,t}]$. Intuitively, equation (13) is equivalent to regressing the error term of the VAR on other error terms according to the lower triangular structure. Equations (13) and (8) form a Gaussian but non linear state space model. However, under the additional assumption of S block diagonal, this problem can be solved by applying the Kalman filter and backward recursion equation by equation.

The third step consists in drawing covariance states, transforming equation (6) in the following equation:

$$A_t(FY_t - Z_t'\Phi_t) = y_t^* = \Sigma_t \epsilon_t \tag{14}$$

This system of nonlinear measurement equations is converted in a linear one, by squaring and taking logarithm of every elements of equation (14). A constant $\bar{c}$ is used to make the estimation procedure more robust. We obtain the following state space form:

$$y_t^{**} = 2h_t + e_t \tag{15}$$

$$h_t = h_{t-1} + \eta_t \tag{16}$$

where $y_{i,t}^{**}$ =log$[(y_{i,t}^*)^2 + \bar{c}]$; $e_{i,t}$ =log$(e_{i,t}^2)$; $h_{i;t}$ =log$\sigma_{i,t}; E[e_t, \eta_t] = 0$. Since $e_t \sim$log$\chi^2(1)$ the system is linear but not Gaussian. In order to convert the system in a Gaussian one, a mixture of seven Normals approximation for any elements of e is used as the variance covaraince matrix of e is diagonal, following the approach in Kim, Shephard and Chib (1998).

3 Identification of Monetary and Fiscal Policy Shocks

The identification of monetary and fiscal policy shocks is achieved by mixing the SVAR approach and the narrative approach. The SVAR approach consists of imposing some restrictions on the reduced-form residuals of a standard VAR, motivated by economic theory. Restrictions can be short term (e.g. the Choleski decomposition), assuming that some variables do not react contemporaneously to a shock, or long term (e.g. Blanchard and Quah (1989)), assuming that only one variable react to the shock in the long run. Another procedure is to apply sign restrictions, which identify the shock by imposing the direction of the impulse responses of certain variables at predefined horizons.[4]. One concern of the SVAR approach in the identification of exogenous policy innovations is that structural shocks may be anticipated by economic agents, resulting in biased estimation. This issue is particularly relevant for fiscal policy, because of the delay between the policy decision and the policy implementation (the so-called “outside lag”).

[4]This method has been introduced by Uhlig (2005) for monetary policy and applied by Mountford and Uhlig (2009) and Pappa (2009) for fiscal policy. Canova and De Nicolo’ (2002) impose sign restrictions on the cross-correlations between the variables in response to shocks, rather than directly on the impulse response functions.

Problems of "fiscal foresight" in macroeconometrics have been subject of study of Ramey (2011) and Forni and Gambetti (2010).

The literature has suggested the narrative approach as alternative methodology for the identification of policy shocks through non-statistical procedures, by extracting information from historical records (such as government reports and speeches, monetary policy committee's documents, international organizations' reports). This approach allows to isolate episodes of exogenous variations of fiscal and monetary variables from endogenous movements induced by business cycles and other non-policy influences. Romer and Romer (1989) introduced this methodology to construct monetary policy innovations, consulting the transcripts from FOMC meetings. Romer and Romer (2010) employ a similar method to identify exogenous tax shocks, examining news, speeches of government officials and other government documents. Ramey and Shapiro (1998), on the basis of contemporary accounts in the press, identify military spending events as a proxy for exogenous shocks to government spending. Devries et al. (2011) extend the historical approach for other OECD countries to identify episodes of fiscal consolidation.

In this study the SVAR approach and the narrative approach are combined in order to evaluate the effects of the interaction of fiscal and monetary policy. Structural shock are identified from the TVP FAVAR model and thanks to the time varying structure of the model a policy shock is simulated in the same month when historical records register another policy shock. In this way we track the reaction of macroeconomic and financial variable to a monetary (or fiscal) shock under different fiscal (or monetary) regimes and we study the complementarity of fiscal and monetary policy.

The identification of innovations in the TVP FAVAR model is achieved using a recursive ordering. First parameters are estimated from the reduced form model and then the structural shocks are recovered. Unobservable factors are sorted before the observed variables (the military date variable, inflation, industrial production and the federal fund rate). The observed factors follow a same order as the one in Christiano et al. (1996), in which the fiscal variable is exogenous with respect to the other macroeconomic variables and the monetary policy instrument, the federal fund rate, reacts to economic activity and inflation following a Taylor rule but it impacts those variables at one lag. To implement this identification scheme we separate slow-moving variables from fast-moving variables in the information set X_t, following Bernanke et al. (2005). First, principal components ($\hat{C}_t^s$) are extracted from slow-moving variables. Second, principal components ($\hat{C}_t$) extracted from the overall information set is regressed on the slow moving factors and the federal fund rate (r_t):

$$\hat{C}_t = b_c \hat{C}_t^s + b_r r_t + e_t \tag{17}$$

Finally, $\hat{F}_t$ is obtained from $\hat{C}_t - \hat{b}_r r_t$ to control for the part of $\hat{C}_t$ that correspond to the federal fund rate. [5]

Fiscal policy shocks are identified through shocks to the military date variable following Ramey and Shapiro (1998). These authors argue that military buildups on the eve of wars, based on forecast of large rises in public spending, can be modeled as expansionary fiscal shocks because occur rapidly and unexpectedly. They show that public spending skyrockets after these

[5] A drawback of the recursive scheme is the assumption that components of estimated factors respond to the monetary and fiscal policy shocks at one lag. An alternative identification is to extract slow-moving and fast moving factors from the respective blocks of data and order slow-moving factors before the observed factors and fast-moving factors last. However, the first principal component of fast-moving variables turn out to be higly correlated with the federal fund rate (the coefficient of correlation = 0.973) and this would introduce collinearity in the system.

episodes and they find that this variable has a considerable predictive power for the growth of the real defense spending. [6] Moreover, they consider military buildups exogenous with respect to macroeconomic variables because driven by imperatives of foreign policy. Krugman disagrees about the assumption that military spending is completely exogenous to the business cycle and argues that war episodes are characterized by good rationing and capacity constraint so that the transmission mechanism of fiscal policy during wartime and peaceful time could be different. As in this analysis we employ monthly data to trace the reaction of financial markets to policy changes and avoid problem of time aggregation, the use of the military dummy variable is the only way to capture exogenous fiscal policy changes. Moreover, our interest is more on the reaction of fiscal markets to unexpected "fiscal news" than to track the consequences of an effective change in public spending on the real economy. [7] Finally Figure 1 shows that not only defense spending growth but also total public spending growth peaks following the military buildups episodes, suggesting that military spending account for a large part of government spending. As the sample used in this analysis starts in 1973:01, the military date variable takes a value of unity in 1980:01 (the Carter-Reagan buildup) and in 2001:10 (the 9/11 buildup). This last epsiode, not considered in Ramey and Shapiro (1998), has been suggested by Fisher (2005) and Ramey (2011)

The response of macroeconomic and financial variables to a monetary shock is evaluated in the same period when a fiscal shock occurred. We identify an expansionary government spending shock using the military date variables. For the impulse response analysis only the government spending shock in 9/11 is considered. This is because differences in the impulse response function in previous periods (e.g. the Carter-Reagan buildup) could be due to structural changes in the US economy and not to different fiscal regimes. The same criterion is adopted for the selection of tax shocks episodes. Reading the historical records of Romer and Romer (2009), we select expansionary tax changes to foster long-term growth and contractionary tax changes to reduce the public deficit. In particular, we choose the *Omnibus Budget Reconciliation Act of 1993* for contractionary tax changes and the *Jobs and the Growth Tax Relief Reconciliation Act* of 2003 for expansionary tax changes. [8]

The *Omnibus Budget Reconciliation Act of 1993*, enacted on August 10, introduced fiscal consolidation measures motivated by deficit reduction. Roughly two-thirds of the additional revenues came from higher marginal rates on high-income individuals (from both the regular income tax and the repeal of the cap on income subject to the Medicare tax). The remaining third came from a wide array of sources. The changes were almost all intended to be permanent. This measure yielded a tax increase of $68.4 billion in 1993Q3. Devries et al. (2011) note that tax hikes were accompanied by spending cuts. Total fiscal consolidation in 1993 amounted to 0.32 percent of GDP, with spending cuts of 0.23 percent of GDP, and tax hikes of 0.08 percent of GDP.

[6] See also Engemann et al. (2008).

[7] To the sake of comparison, the American Recovery and Reinvestment Act (ARRA), enacted in February 2009, is the biggest fiscal stimulus of the U.S. history, but is highly endogenous to the state of the economy and probably largely anticipated by economic agents, because of the debate preceded in the economic press. So it cannot be considered as an unexpected fiscal shock.

[8] Another important episode of tax hikes was the *Omnibus Budget Reconciliation Act of 1987*, motivated by deficit reduction and putting the social security system on a sustainable footing. The tax hike had an estimated budgetary impact of $10.8 billion (p. 77). However, these tax hikes were partly offset by a tax cut associated with the *Tax Reform Act of 1986*. As Romer and Romer (2009) explain, this tax cut was motivated by the need to simplify the tax system, and not in response to short-term economic developments, and the budgetary impact was –$7.2 billion. Therefore, the net tax hike amounted to $3.6 billion (10.8–7.2) in 1988. For this reason we do not include this episode.

The *Jobs and the Growth Tax Relief Reconciliation Act*, signed on May 28 2003, reduced marginal rates, lowered taxes on dividends, and increased investment incentives. The investment incentives were intended to be temporary. The other provisions were legislated as temporary (although the dividend cuts were scheduled to last a substantial time), but it is clear that their supporters intended them to be permanent. The tax cuts were motivated by long-run and short-run considerations. In 2003Q3 the tax cut amounted to $126.4 billions, the biggest one in the U.S. postwar era.

Finally, to compare results under different fiscal regimes we consider the 06:2006 as a benchmark for the impulse response analysis. There are not economic reasons for the choice of this benchmark, except that no fiscal and monetary policy shocks are registered in this period.

Concerning the study of fiscal policy shocks under different monetary regimes, we cannot rely on historical records of episodes of exogenous monetary policy, since the study of Romer and Romer (1989) covers only a small part of the sample used in this analysis. For this reason we compare the impact of a fiscal shock in normal times and with the zero lower bound.

4 Results

Figures 4-7 display the median of the posterior distributions of the impulse responses to a negative monetary policy shock under different fiscal regimes. Figure 4 compares the impact of a monetary shock on macroeconomic variables with and without an expansionary government spending shock (green line and blue line respectively). In both cases the response of inflation is negative and persistent, so the price puzzle disappears when the VAR model is augmented with principal components extracted from of a large information set. The response of industrial production differs in the two scenarios. In "normal times" economic activity falls after a tightening in monetary policy. However, when a negative policy shock is combined with a positive Government spending shock the response of industrial production is slightly positive for 11 months and then becomes negative. The graph shows clearly that the impact of a change in monetary policy on the industrial production varies under different fiscal policy regimes. In particular, the contractionary effect of a negative monetary policy shock is offset by the expansionary effect of a positive government spending shock. In other words, an accommodative monetary policy cannot stimulate the economic activity in the short run if combined with a fiscal adjustment based on spending cuts, which is the policy mix currently adopted in UK and in most of the European countries.

Figure 5 shows the effects of a monetary policy shock on macroeconomic variables in conjunction with an expansionary tax shock (green line) and a contractionary tax shock (red line). The response of inflation is negative, in all the scenarios. Similarly, industrial production declines, but with different shape in the three cases. The contraction of economic activity is stronger with a negative tax shock than with an expansionary tax shock. In the latter case the reaction is almost null. Comparing the impulse response function of the economic activity with an expansionary government spending shock and with an expansionary tax shock, we can note that in the first case the policy mix is more effective in sustaining the economic activity.

Figure 6 plots the response of financial variables to a negative monetary policy shock combined with a positive government spending shock. Equity prices increase after the monetary shock, although the response is dampened with the occurrence of a positive Government spending shock. The response of the long term interest rate, represented by the 10-year Treasury rate, closely tracks the response of the federal fund rate and no differences appear under different fiscal regimes. We compare the impact of a monetary policy shock on three different spreads: the BAA-AAA spread, the TED spread and the external risk premium. Figure 3 displays the sudden rise in these spreads during the recent financial crisis. The BAA-AAA spread, the difference between the BAA corporate bond yields and the AAA corporate bond yields, is a measure of credit spread which indicates that the BAA securities become less liquid. Hence, a spike of this index suggests a period of stress in credit markets. The TED spread is the difference between the risky 3-month LIBOR rate and the risk-free 3-month Treasury bill rate and is a proxy for U.S. liquidity pressure. Further, Treasury bonds become more attractive, as banks want to get first-rate collateral, and the Treasury bond yield fall. Figure 3 shows that in times of financial stress the TED spread widens because banks charge higher interest for unsecured loans, which increases the LIBOR rate. This happened in August 2007 and in October 2008 after the collapse of Lehman Brother, showing signs of credit market deteriorations. The external finance premium, the difference between the bank prime loan and the 3-month Treasury bill rate, measures the premium that firms pay when raise funds externally asking a credit to banks. Taken together, these indicators are a proxy of financial conditions. The BAA-AAA spread and the external finance premium spike on impact but after 2 months the effect is negative and persistent. The reaction of the TED spread to a monetary policy shock is positive and revert to its initial level slowly. The response of spreads to a negative monetary policy shock seems not affected by the occurrence of a positive government spending shock.

Figure 7 displays the impact of a negative monetary policy shock on financial variables with an expansionary and a contractionary tax shocks. The reaction of equity prices to a monetary policy shock is positive with an expansionary tax shock and contractionary with a negative tax shock, suggesting that the sign of the impulse response function depends on the stance of fiscal policy. The response of the other financial variables, is analogous in the different fiscal scenarios, except for the reaction of the BAA-AAA spread and TED spread to a policy mix of negative monetary policy and positive fiscal policy. In this case spreads are higher than with a neutral and an expansionary fiscal policy.

To sum up we observe the reaction of economic activity to a monetary policy shock varies when combined with different fiscal policy shock. In particular the contractionary effect of a negative positive shock is mitigated by a positive fiscal shock. The reaction of economic activity to different policy mix is consistent with a textbook IS-LM model. Moreover, a positive government spending shock seems more expansionary than a positive tax shock. The fiscal policy shocks have a low impact on financial variables, as we do not observe significant difference in the impulse responses of a monetary policy shock with and without a government spending shock or a tax shock. An exception is the response of equity prices, which is expansionary with a positive government spending shock and a negative tax shock and contractionary with a positive tax shocks.

5 Conclusions

A large part of the literature examines the evolution of monetary policy over the past years applying econometric models with time varying parameters. This paper uses a Time Varying Parameters Factor Augmented VAR model to study the interaction of fiscal and monetary policy. The time varying structure of the model allows to simulate the impact of a monetary policy shock, identified with the SVAR approach, in the same period of the occurrence of a fiscal shock, identified with the narrative approach. In this way we can study the impact of monetary policy under different fiscal policy regimes.

A second main contribution of this paper is that, by including factors in the model, extends the impulse response analysis on several financial variables, which played a key role in the propagation and amplification of a financial shock during the recent financial crisis. Studying the reaction of financial variables to different combination of policy shocks may provide new insights on the transmission mechanism of monetary and fiscal policy.

Results show that the contractionary effect of a negative monetary policy shock can be offset by a positive government spending shock or a positive tax shock. They also suggest that a loose monetary policy cannot stimulate the economy in the short run when combined with a fiscal adjustment, especially if based on spending cuts

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Data

The dataset contains macroeconomic and financial variables spanning from 01:1973 to 01:2012. All series are downloaded from St. Louis' FRED database and they are seasonally adjusted (either by taking seasonally adjusted from the original sources or by applying the X-12-ARIMA seaonal adjustment program of the U.S. Census Bureau). Spreads are calculated by the author. All variables are transformed to be approximate stationary. The transformation codes are: 1 - no transformation; 2 - first difference; 4 - logarithm; 5 - first difference of logarithm. Following Bernanke et al. (2005), the fast moving variables are interest rates, stock returns, exchange rates, monetary aggregates and loans. Slow = 1 indicates that a variable is slow-moving. All variable descriptions and pneumonics are from the original source, except spreads.

Table 1: Information set

No.serie	Mnemonic	Slow	Transformation	Description
1	AHETPI	1	5	Aver. Hourly Earn. of Prod. and Nonsuperv. Employees
2	AMBSL	0	5	St. Louis Adjusted Monetary Base
3	CANDH	1	1	Chicago Fed Nat. Act. Index: Personal Consumpt. and Hous.
4	CFNAI	1	1	Chicago Fed Nat. Act. Index
5	DSPI	1	5	Disposable Personal Income
6	EMRATIO	1	1	Civilian Employment-Population Ratio
7	HOUST	0	4	Housing Starts: Total: New Priv. Owned Housing Units Started
8	HOUST1F	0	4	Privately Owned Housing Starts: 1-Unit Structures
9	HOUST2F	0	4	Housing Starts: 2-4 Units
10	HOUST5F	0	4	Privately Owned Housing Starts: 5-Unit Structures or More
11	M1SL	1	5	M1 Money Stock
12	M2SL	1	5	M2 Money Stock
13	PANDI	1	1	Chicago Fed National Activity Index: Production and Income
14	PAYEMS	1	5	All Employees: Total nonfarm
15	PCE	1	5	Personal Consumption Expenditures
16	PCEDG	1	5	Personal Consumption Expenditures: Durable Goods
17	PCEND	1	5	Personal Consumption Expenditures: Nondurable Goods
18	PCES	1	5	Personal Consumption Expenditures: Services
19	PERMIT	1	4	New Private Housing Units Authorized by Building Permits
20	SOANDI	1	1	Chicago Fed National Activity Index: Sales, Orders and Invent.
21	TCU	1	1	Capacity Utilization: Total Industry
22	UNEMPLOY	1	5	Unemployed
23	UNRATE	1	1	Civilian Unemployment Rate
24	USEHS	1	5	All Employees: Education & Health Services
25	USFIRE	1	5	All Employees: Financial Activities
26	USGOVT	1	5	All Employees: Government
27	USINFO	1	5	All Employees: Information Services
28	USLAH	1	5	All Employees: Leisure & Hospitality
29	USPRIV	1	5	All Employees: Total Private Industries
30	USSERV	1	5	All Employees: Other Services
31	USTRADE	1	5	All Employees: Retail Trade
32	USWTRADE	1	5	All Employees: Wholesale Trade
33	SP500	0	5	S&P 500 Stock Price Index
34	DJIA	0	5	Dow Jones Industrial Average
35	DJUA	0	5	Dow Jones Utility Average
36	DJCA	0	5	Dow Jones Composite Average
37	NFCI	0	1	Chic. Fed Nat. Financ. Condit. Index
38	NFCICREDIT	0	1	Chic. Fed Nat. Financ. Condit. Credit Subindex
39	NFCILEVERAGE	0	1	Chic. Fed Nat. Financ. Condit. Leverage Subindex
40	NFCIRISK	0	1	Chic. Fed Nat. Financ. Condit. Risk Subindex
41	NFCINONFINLEVERAGE	0	1	Chic. Fed Nat. Financ. Condit. Index Nonf. Leveral Subindex
42	CONSUMER	0	5	Consumer Loans at All Commercial Banks
43	TOTALSL	0	5	Total Consumer Credit Owned and Securitized, Outstanding
44	DED3	0	2	3-Month Eurodollar Deposit Rate (London)
45	EXCRESNS	0	5	Excess Reserves of Depository Institutions
46	CPILFESL	1	5	C.P.I. for All Urban Consumers: All Items Less Food & Energy
47	CPIULFSL	1	5	C.P.I. for All Urban Consumers: All Items Less Food
48	CPILEGSL	1	5	C.P.I. for All Urban Consumers: All Items Less Energy
49	CPIENGSL	1	5	C.P.I. for All Urban Consumers: Energy
50	CPIUFDSL	1	5	C.P.I. for All Urban Consumers: Food
51	PPICPE	1	5	Producer Price Index: Finished Goods: Capital Equipment

No.serie	Transformation	Mnemonic	Slow	Description
52	PPICRM	1	5	Producer Price Index: Crude Materials for Further Processing
53	PPIFCG	1	5	Producer Price Index: Finished Consumer Goods
54	PPIFGS	1	5	Producer Price Index: Finished Goods
55	SRVPRD	1	5	All Employees: Service-Providing Industries
56	USGOOD	1	5	All Employees: Goods-Producing Industries
57	USPRIV	1	5	All Employees: Total Private Industries
58	CE16OV	1	5	Civilian Employment
59	CLF16OV	1	5	Civilian Labor Force
60	CIVPART	1	1	Civilian Labor Force Participation Rate
61	AWOTMAN	1	1	Aver. Weekly Overtime Hours of Prod. and Nonsup. Employees: Manufact.
62	AWHMAN	1	1	Aver. Weekly Hours of Production and Nonsupervisory Employees: Manufact.
63	IPNCONGD	1	5	Industrial Production: Nondurable Consumer Goods
64	IPMAT	1	5	Industrial Production: Materials
65	IPFINAL	1	5	Industrial Production: Final Products (Market Group)
66	IPDCONGD	1	5	Industrial Production: Durable Consumer Goods
67	IPCONGD	1	5	Industrial Production: Consumer Goods
68	IPBUSEQ	1	5	Industrial Production: Business Equipment
69	UEMP5TO14	1	5	Civilians Unemployed for 5-14 Weeks
70	UEMP15OV	1	5	Civilians Unemployed - 15 Weeks & Over
71	UEMP15T26	1	5	Civilians Unemployed for 15-26 Weeks
72	UEMP27OV	1	5	Civilians Unemployed for 27 Weeks and Over
73	TB3M	0	1	3-Month Treasury Bill: Secondary Market Rate
74	AAA'	0	1	AAA Moody's Seasoned Aaa Corporate Bond Yield
75	BAA'	0	1	Moody's Seasoned Baa Corporate Bond Yield
76	CD3M'	0	1	3-Month Certificate of Deposit: Secondary Market Rate
77	CD6M'	0	1	6-Month Certificate of Deposit: Secondary Market Rate
78	EXCAUS	0	5	Canada / U.S. Foreign Exchange Rate
79	EXJPUS	0	5	Japan / U.S. Foreign Exchange Rate
80	EXSDUS	0	5	Sweden / U.S. Foreign Exchange Rate
81	EXSZUS	0	5	Switzerland / U.S. Foreign Exchange Rate
82	GS1	0	1	1-Year Treasury Constant Maturity Rate
83	GS10	0	1	10-Year Treasury Constant Maturity Rate
84	GS3	0	1	3-Year Treasury Constant Maturity Rate
85	GS5	0	1	1-Month Eurodollar Deposit Rate (London)
86	MED1	0	1	3-Month Eurodollar Deposit Rate (London)
87	MED3	0	1	5-Year Treasury Constant Maturity Rate
88	MED6	0	1	6-Month Eurodollar Deposit Rate (London)
89	MORTG	0	1	30-Year Conventional Mortgage Rate
90	MPRIME	0	1	Bank Prime Loan Rate
91	TB6MS	0	1	6-Month Treasury Bill
92	sTB6MS	0	1	sTB6MS Spread 6-Month Treasury Bil - Federal Fund Rate
93	sGS1	0	1	Spread 1-Year Treasury Constant Maturity Rate - Fed Fund Rate
94	sGS10	0	1	Spread 10-Year Treasury Constant Maturity Rate - Fed Fund Rate
95	sGS3	0	1	Spread 3-Year Treasury Constant Maturity Rate - Fed Fund Rate
96	sGS5	0	1	sGS5 Spread 5-Year Treasury Constant Maturity Rate - Fed Fund Rate
97	sMPRIME	0	1	Spread Bank Prime Loan Rate - Fed Fund Rate
98	sAAA	0	1	Moody's Seasoned Aaa Corporate Bond Yield - Fed Fund Rate
99	sBAA	0	1	sBAA Moody's Seasoned Aaa Corporate Bond Yield - Fed Fund Rate
100	BUSLOANS	0	5	Commercial and Industrial Loans at All Commercial Banks
101	INVEST	0	5	Total Investments at All Commercial Banks
102	LOANINV	0	5	Bank Credit at All Commercial Banks
103	LOANS	0	5	Loans and Leases in Bank Credit
104	REALLN	0	5	Real Estate Loans at All Commercial Banks
105	USGSEC	0	5	Treasury and Agency Securities at All Commercial Banks
106	OTHSEC	0	5	Other Securities at All Commercial Banks
107	BAA-AAA	0	1	Default Rate Spread
108	MPRIME-TB3MS	0	1	External Finance Premium
109	LIBOR3M-TB3M	0	1	TED spread

Appendix A: Figures

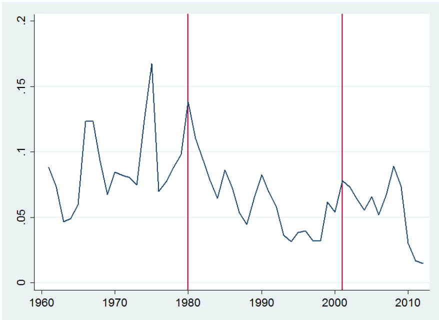

Figure 1: Military buildups and total Government spending growth. The red lines indicate the episodes of military buildups in 1980 and 2001.

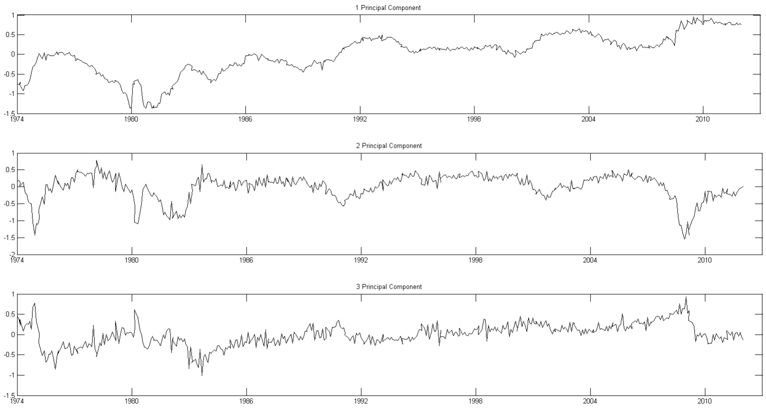

Figure 2: Principal components extracted from X_t

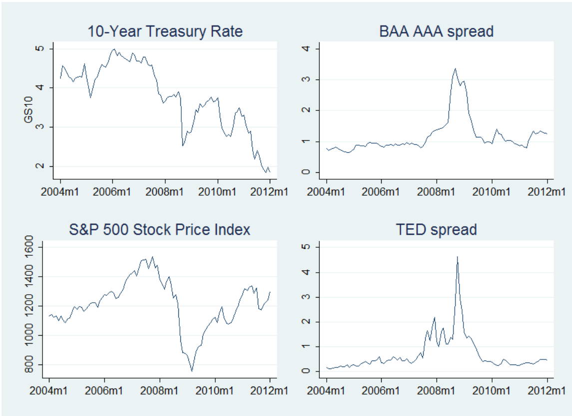

Figure 3: Financial variables during the crisis

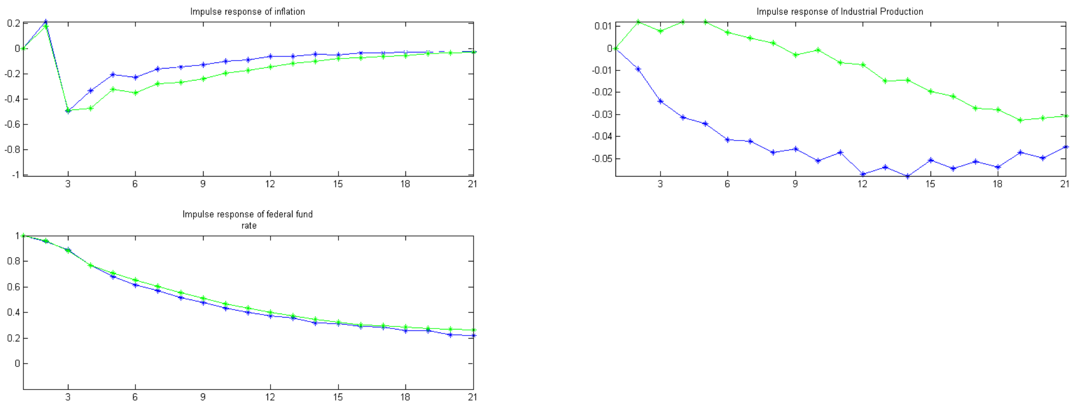

Figure 4: Impulse responses of macroeconomic variables to a negative monetary policy shock with and without a government spending shock. The green line represents the impulse reponse with an expansionary government spending shock (2001:10) and the blue line without a government spending shock (2006:06)

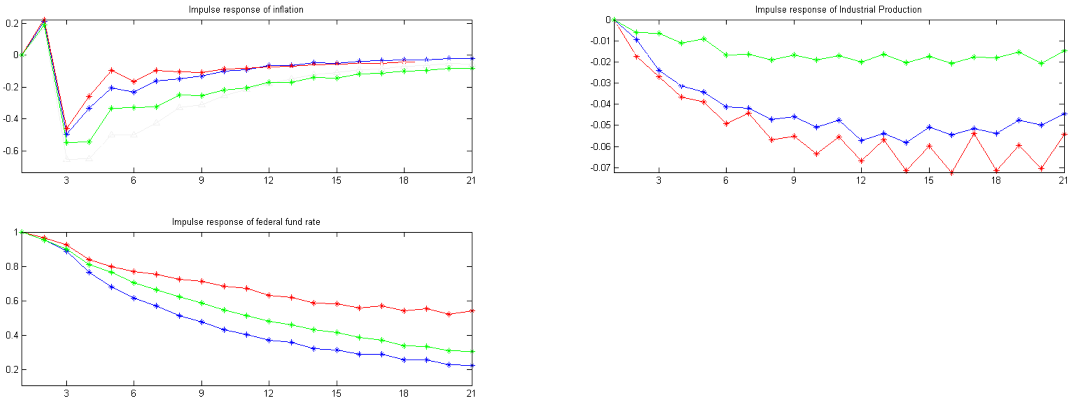

Figure 5: Impulse responses of macroeconomic variables to a negative monetary policy shock with and without a tax shock. The green line represents the impulse response with an expansionary tax shock (1993:11), the red line with a contractionary tax shock (2003:06) and the blue line without a tax shock (2006:06)

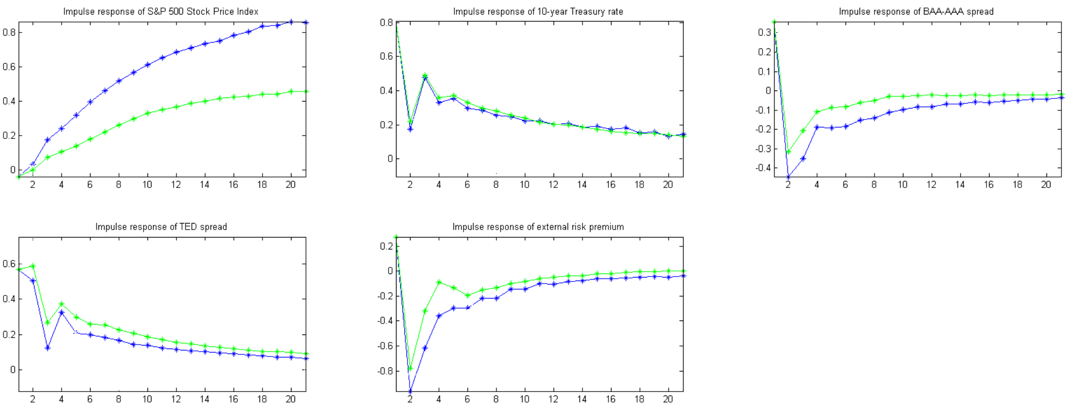

Figure 6: Impulse responses of financial variables to a negative monetary policy shock with and without a government spending shock. The green line represents the impulse reponse with an expansionary government spending shock (2001:10) and the blue line without a government spending shock (2006:06)

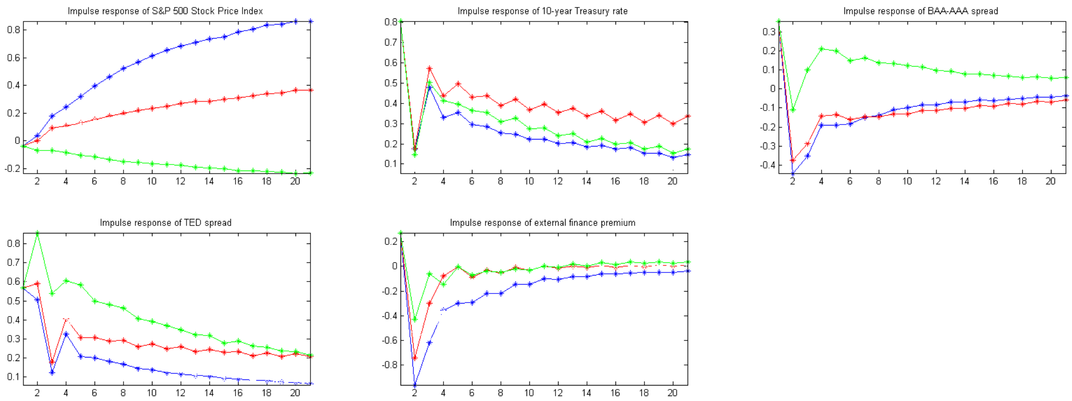

Figure 7: Impulse responses of financial variables to a negative monetary policy shock with and without a tax shock. The green line represents the impulse response with an expansionary tax shock (1993:11), the red line with a contractionary tax shock (2003:06) and the blue line without a tax shock (2006:06)

Appendix: The Markov Chain Monte Carlo algorithm

This section presents the Gibbs sampling procedure applied to estimate the time varying parameters. This method follows Primiceri (2005) and it is described in Kim and Nelson (1999). Consider a linear and Gaussian state space form:

$$
\begin{aligned}
&y_t = Z\beta_t + e_t \\
&\beta_t = T\beta_{t-1} + v_t \\
&e_t \sim i.i.d.N(0, Q_t) \\
&v_t \sim i.i.d.N(0, H) \\
&E(e_t, v_t') = 0
\end{aligned}
$$

Let $\beta_{t|s} = E(\beta_t|Y^s, H^s, R^s, Q)$ and $V_{t|s} = Var(\beta_t|Y^s, H^s, R^s, Q)$. Then, given $\beta_{0|0}$ and $V_{0|0}$, a standard Kalman filter delivers:

$$
\begin{aligned}
&\beta_{t|t-1} = T\beta_{t-1|t-1} \\
&P_{t|t-1} = TP_{t-1|t-1}T' + Q \\
&v_t = y_{t|t-1} - Z\beta_{t|t-1} \\
&F_{t|t-1} = ZP_{t|t-1}Z' + H \\
&\beta_{t|t} = \beta_{t|t-1} + P_{t|t-1}Z'F_{t|t-1}^{-1}v_t \\
&P_{t|t} = P_{t|t-1} - P_{t|t-1}Z'F_{t|t-1}^{-1}ZP_{t|t-1}
\end{aligned}
$$

The last elements of the recursion are $\beta_{T|T}$ and $V_{T|T}$, which are the mean and the variance of the normal distribution used to make a draw for β_T. The draw of β_T and the output of the filter are now used for the first step of the backward recursion, which provides $\beta_{T|T-1}$ and $V_{T|T-1}$, used to make a draw of β_{T-1}. The backward recursion continues until time zero. For a generic time t, the updating formulas of the backward recursion are:

$$
\begin{aligned}
&\beta_{t|t+1} = \beta_{t|t}P_{t|t}F'P_{t+1|t}^{-1}(\beta_{t+1} - T\beta_{t|t}) \\
&V_{t|t+1} = V_{t|t} - V_{t|t}F'P_{t+1|t}^{-1}FV_{t|t}
\end{aligned}
$$