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Abstract

This paper analyzes jointly the effects of monetary and fiscal policy shocks in the US economy using a factor augmented vector autoregressive model with drifting coefficients and stochastic volatility. The time varying structure of the model allows to assess the impact of monetary policy shocks in the same periods when fiscal policy shocks identified via the narrative approach are also at play. In this way we study how the monetary policy transmission changes conditional on expansionary or contractionary exogenous fiscal policies, which are determined by the discretionary intervention of the fiscal authority and are not the response of business cycle fluctuations or the reaction to monetary policy. We find that fiscal policy strongly affects the impulse responses to monetary policy shocks through the aggregate demand channel. These results are relevant to understand the implications of different policy mixes.

Keywords

TVP FAVAR, monetary policy shocks, fiscal policy shocks

JEL codes: E52, E62, E63, E65, C32

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1 Introduction

During the recent financial crisis and the Great Recession central banks implemented unprecedented monetary policies to stabilize the financial markets and sustain economic activity. At the same time, fiscal authorities intervened with fiscal stimuli to spur aggregate demand before turning to austerity measures to contain growing public deficits. Since the US economy has been recovering from the crisis, the Federal Reserve is normalizing the conduct of monetary policy and has started to lift the policy rate, abandoning the zero lower bound. Coincidently, the Trump administration unveiled a $ 1 trillion plan in public infrastructure. Understanding the effects of these measures requires therefore a *joint* analysis of monetary and fiscal policies.

Nevertheless, most of the empirical studies used to evaluate the consequences of macroeconomic policies are based on structural vector autoregressions (SVARs), which recover orthogonal monetary and fiscal policy shocks to trace out alternately their impact on the economy, without the possibility of examining the effects of their interplay.[1] They assess the consequences of monetary policy, regardless of the implementation of fiscal policy that may alter the dynamics of economic variables, and viceversa.

In this paper we propose a novel approach to address this issue by studying the effects of a simultaneous combination of monetary and fiscal policy shocks. Using a Time Varying Parameter Factor Augmented VAR model (TVP-FAVAR), we estimate the impulse response function of a monetary policy shock in the same period as when the US economy is hit by a fiscal policy shock identified with ex-

[1]Exceptions are Canova and Pappa (2011) and Gerba and Hauzenberger (2013) who use sign restrictions to investigate the fiscal-monetary interactions.

ternal information based on the "narrative" approach. This methodology consists of defining exogenous shifts in fiscal policy variables by reading official documents which report information about the reason, size and timing of fiscal actions. In particular we rely on two sources: Romer and Romer (2010) for tax shocks and Ramey (2011) for government spending shocks. Romer and Romer (2010) identify tax shocks by distinguishing exogenous tax variations motivated by the desire to reduce the public deficit (contractionary tax shocks), or to spur the long run growth (expansionary tax shock), from countercyclical or spending driven endogenous tax variations, by reading presidential speeches and Congressional reports. In the same vein, Ramey (2011), on the basis of contemporary accounts in the press, constructs a defense news variable based on changes in government spending that are linked to political and military events, which are independent of the state of the economy, extending the "war dates" of Ramey and Shapiro (1998).

The presence of automatic stabilizers, together with the endogenous and systematic response of fiscal authorities to cyclical conditions (Galí and Perotti (2003)), make fiscal policy strongly countercyclical, creating a tight interaction with monetary policy. For instance, contractionary monetary policy, which depresses the economic activity, leads to an expansion of the public deficit without any intervention of the fiscal authorities by increasing automatically the spending in unemployment benefits and reducing the tax revenues.[2] Further, higher interest payments tighten the government's intertemporal budget constraint; the fiscal authority can react by increasing the primary balance through higher taxes and/or lower expenditure in order to stabilize the budget deficit, or in a non-Ricardian economy by reducing

[2] Coricelli, Fiorito, and Molteni (2017) show that in OECD countries around 70 percent of public expenditure acts de facto as automatic stabilizer.

the primary balance to offset the contractionary effect of monetary policy.[3] Our approach permits to study the monetary policy transmission conditional on different fiscal actions, which are instead determined by the discretionary and exogenous intervention of the fiscal authority and are not state-dependent.[4]

One strand of the literature analyzes how the transmission of fiscal policy varies conditional on the economic environment (Auerbach and Gorodnichenko (2012), Corsetti, Meier, and Müller (2012) Ilzetzki, Mendoza, and Végh (2013), Owyang, Ramey, and Zubairy (2013)), and when monetary policy is constrained by the zero lower bound (Christiano, Eichenbaum, and Rebelo (2011), Woodford (2011)). Canova and Pappa (2011), using different patterns of sign restrictions, study the impact of a fiscal stimulus when monetary policy is accommodative or strongly reacts to inflation. Gerba and Hauzenberger (2013) extend their approach in a time varying framework to analyze how the coordination between fiscal and monetary policies changes over time in US. Rossi and Zubairy (2011) find that the dynamics of a monetary policy shock estimated with a SVAR changes drastically when the model omits a fiscal policy variable and conclude that "failing to recognize that both monetary and fiscal policy simultaneously affect macroeconomic variables might incorrectly attribute the fluctuations to the wrong source." We proceed one step forward and we study the monetary policy transmission, taking into account

[3] These interdependencies between monetary and fiscal policy are the object of study of several contributions which analyze the effect of active or passive monetary and fiscal policy regimes (Leeper (1991), Davig and Leeper (2011), Afonso and Toffano (2013), Kaplan, Moll, and Violante (2016)). An implicit assumption of this paper is that monetary and fiscal authorities act independently.

[4] Blanchard and Perotti (2002) identify three components in the reduced form equations for taxes and government spending shocks: i) the responses of fiscal variables to fluctuations in macroeconomic variables due to automatic stabilizers, ii) the discretionary response of fiscal policy to news in macroeconomic variables and iii) exogenous shifts in taxes and spending. The narrative approach aims at capturing only the latter element.

ex ante the impact of fiscal policy.

Factor models have been increasingly employed in empirical analyses on the effects of monetary policy since they can summarize the dynamics of a large set of variables (see Bernanke and Boivin (2003) Favero and Marcellino (2001), Giannone, Reichlin, and Sala (2002), Giannone, Reichlin, and Sala (2005), Marcellino, Favero, and Neglia (2005)). SVAR models including few time series are likely to suffer problems of omitted variables and information sufficiency (Forni and Gambetti (2014)), since monetary authorities have access to a much larger information set than the variables included in the SVAR.[5] We show that the standard deviation of reduced form residuals drastically reduces when we augment a small-scale time varying parameter VAR with unobserved factors. Bernanke, Boivin, and Eliasz (2005) is the seminal paper that combines VAR with factor analysis (FAVAR). We follow their approach to identify a monetary policy shock based on the distinction between the reaction of slow-moving and fast-moving variables; and we exploit the factor structure to assess the impulse response function on several variables, in order to investigate why the transmission mechanism of a monetary policy shock changes when it coincides with exogenous fiscal policy changes.

We increment their model allowing for time varying parameters. Several papers analyze the transmission mechanism of monetary policy in a time varying framework (Cogley and Sargent (2005), Primiceri (2005), Canova and Gambetti (2006), Gambetti, Pappa, and Canova (2008), Benati (2008)). Furthermore, Eickmeier, Lemke, and Marcellino (2011), Korobilis (2013), Liu, Mumtaz, and Theophilopoulou (2011) use a FAVAR with time-varying parameters (TVP-

[5] An alternative approach is considering VARs with Bayesian shrinkage (see Banbura, Giannone, and Reichlin (2010), Carriero, Clark, and Marcellino (2015), Giannone, Lenza, and Primiceri (2015) for applications in monetary policy).

FAVAR), which is the methodology that we apply.[6] Nevertheless these studies aim to evaluate how the transmission of a shock evolves over time and to detect possible structural breaks. By contrast, in this paper the time-varying structure of the model is crucial to compare the impulse response function of a monetary policy shock joint with different fiscal policy shocks. Our approach can be thought similar to Galí and Gambetti (2015), who using a SVAR with time varying parameters, analyze the impact of a monetary policy shock along different phases of the financial cycle and in particular with the presence of asset bubbles.

Our findings lend support to a strong impact of fiscal policy which affects the transmission mechanism of monetary policy through the aggregate demand channel, especially with tax shocks. In particular, expansionary and contractionary fiscal policy shocks shift labor supply and labor demand in opposite directions, following a contractionary monetary policy shock. As a result, the response of unemployment to monetary policy is highly sensitive to the stance of fiscal policy. Furthermore, when the monetary policy shock is combined with tax shock the adjustment of the labor market differs markedly from the case in which the monetary policy shock occurs with government spending shock, especially for labor demand. The impulse response functions of employment and average weekly hours to monetary policy shock exhibit heterogeneous patterns when combined with tax shocks with different signs.

The remainder of the paper is organized as follows: Section 2 introduces the TVP-FAVAR model and explains the estimation procedure; Section 3 discusses the identification of monetary and fiscal policy shocks; Section 4 shows the empirical

[6] Del Negro and Otrok (2008) develop a dynamic factor model with time-varying factor loadings and stochastic volatility. Pereira and Lopes (2010) and Kirchner, Cimadomo, and Hauptmeier (2010) apply a TVP-VAR for fiscal policy.

results and Section 5 concludes.

2 Methodology

2.1 The Model

The model is a FAVAR with drifting coefficients and stochastic volatility, composed by a factor equation and a VAR equation. The factor equation is

$$\boldsymbol{x_t} = \boldsymbol{\lambda^x} \boldsymbol{f_t^x} + \boldsymbol{\lambda^y} \boldsymbol{f_t^y} + \boldsymbol{u_t} \tag{1}$$

where $\boldsymbol{f_t^y}$ is a (m x 1) vector of observable economic variables that are typically included in a small-scale monetary VAR. Following Cogley and Sargent (2005), Primiceri (2005), Cogley, Primiceri, and Sargent (2010), we consider inflation, unemployment and short-term interest rate. We use monthly data spanning January 1961 through January 2016. $\boldsymbol{x_t}$ is a (n x 1) vector of macroeconomic and financial variables ($n >> m$). This large information set is summarized by $\boldsymbol{f_t^x}$ a (k x 1) vector of unobserved factors which represents forces that affect economic variables included in $\boldsymbol{x_t}$ simultaneously. $\boldsymbol{\lambda^x}$ and $\boldsymbol{\lambda^y}$ are factor loading matrices of dimensions (n x k) and (n x m) respectively, relating $\boldsymbol{f_t^x}$ and $\boldsymbol{f_t^y}$ to $\boldsymbol{x_t}$. The errors $\boldsymbol{u_t}$ have mean 0 and covariance $\boldsymbol{\Omega}$, which is assumed to be diagonal. The errors $\boldsymbol{u_t}$ are assumed to be uncorrelated with the unobserved factors $\boldsymbol{f_t^x}$ and observed factors $\boldsymbol{f_t^y}$ at all leads and lags and mutually uncorrelated at all leads and lags, namely $E[\boldsymbol{u_{i,t}} \boldsymbol{f_t^x}] = E[\boldsymbol{u_{i,t}} \boldsymbol{f_t^y}] = E[\boldsymbol{u_{i,t}} \boldsymbol{u_{j,s}}] = 0$ for all i, j=1,...,n ∧ t, s=1,..,t and i≠j ∧ t≠s.

Let $\boldsymbol{y_t} = [\boldsymbol{f_t^{x'}}, \boldsymbol{f_t^{y'}}]$ a vector of dimension (q x 1) with q = m + k, including unobserved and observed factors. The TVP-FAVAR can be expressed as a VAR(p) process with drifting coefficients and stochastic volatilities describing the joint dynamics of $\boldsymbol{y_t}$

$$\boldsymbol{y_t = b_{1,t}y_{t-1} + ... + b_{p,t}y_{t-p} + v_t} \tag{2}$$

$\boldsymbol{v_t}$ follows a white noise Gaussian process with mean zero and covariance matrix $\boldsymbol{\Sigma_t}$. The time varying coefficients can be collected in $\boldsymbol{B_t}$ which follows a driftless random walk

$$\boldsymbol{B_t = B_{t-1} + \eta_t^B} \tag{3}$$

where $\boldsymbol{\eta_t^B}$ is a Gaussian white noise process with zero mean and constant covariance matrix $\boldsymbol{\Gamma}$ which determines the degree of variability of the coefficients. Following Primiceri (2005), we model the time variation of $\boldsymbol{\Sigma_t}$ as follows

$$\boldsymbol{\Sigma_t = A_t^{-1} H_t H_t' (A_t')^{-1}} \tag{4}$$

We can express $\boldsymbol{A_t v_t = H_t \epsilon_t}$ with $E[\boldsymbol{\epsilon_t \epsilon_t'}] = I$ and $E[\boldsymbol{\epsilon_t \epsilon_{t-k}'}] = 0$. The contemporaneous relations of the shocks and the factors are represented through the matrix $\boldsymbol{A_t}$ of dimension (q x q). From the above triangular reduction it follows that

$$\boldsymbol{A_t} = \begin{bmatrix} 1 & 0 & \dots & 0 \\ \alpha_{21,t} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ \alpha_{q1,t} & \dots & \alpha_{qq-1,t} & 1 \end{bmatrix} \quad ; \quad \boldsymbol{\Sigma_t} = \begin{bmatrix} \sigma_{1,t} & 0 & \dots & 0 \\ 0 & \sigma_{2,t} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \dots & 0 & \sigma_{q,t} \end{bmatrix}$$

We collect the non-zero elements $\alpha_{i,t}$ and $h_{i,t}$ into $\boldsymbol{\alpha_t}$ and $\boldsymbol{h_t}$ and assume that they evolve as driftless random walks and geometric random walk, respectively

$$\boldsymbol{\alpha_t} = \boldsymbol{\alpha_{t-1}} + \boldsymbol{\eta_t^\alpha} \tag{5}$$

$$log\ \boldsymbol{h_t} = log\ \boldsymbol{h_t} + \boldsymbol{\eta_t^h} \tag{6}$$

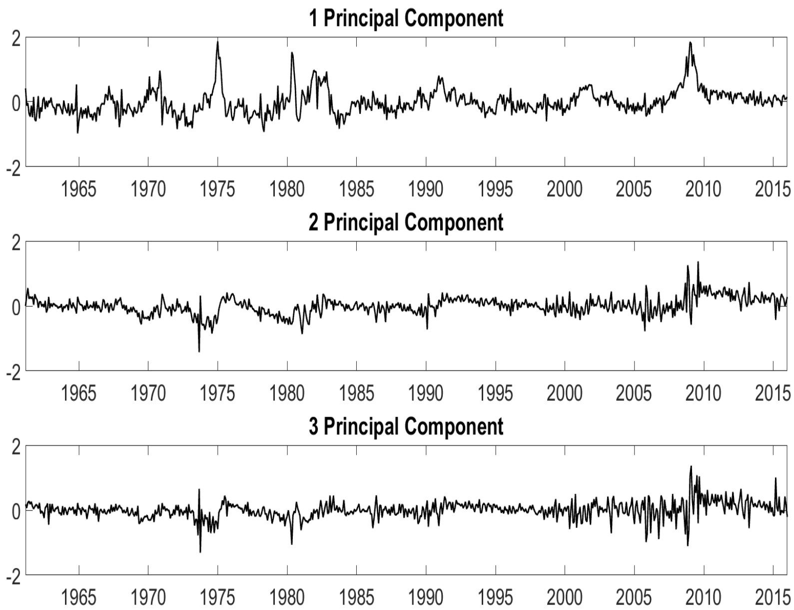
where $\boldsymbol{\eta_t^\alpha}$ and $\boldsymbol{\eta_t^h}$ are white noise Gaussian process with zero mean and constant covariance matrices $\boldsymbol{\Xi}$ and $\boldsymbol{\Psi}$, respectively. We assume that $\boldsymbol{\eta_t^h}, \boldsymbol{\eta_t^h}, \boldsymbol{\eta_t^h}, \boldsymbol{\epsilon_t}$ are mutually uncorrelated at all leads and lags and $\boldsymbol{\Xi}$ is restricted to be block diagonal, where each block corresponds to parameters belonging to separate equations. This system reduces to a FAVAR with constant parameters setting $\boldsymbol{\Gamma} = \boldsymbol{\Xi} = \boldsymbol{\Psi} = 0$.

2.2 Estimation

The model can be represented in a state-space form in which the measurement equation is the factor equation and the state equation is the VAR equation. We estimate the model in two stages. The first stage involves estimating the unobserved factors $\boldsymbol{f_t^x}$ as first principal components of $\boldsymbol{X_t}$. The second stage consists of including the estimated principal components $\boldsymbol{P\hat{C}_t}$ in the VAR and estimate the time-varying parameter via Bayesian methods. An alternative one-step procedure consists of estimating equations (1) and (2) simultaneously by Gaussian maximum likelihood (ML) or Quasi ML using the Kalman filter. Doz, Giannone, and Reichlin (2012) show that ML estimates of the common factors are also consistent for large cross-sectional and time dimension.

The advantage of the two-step procedure is that, being semiparametric, it requires weaker distributional assumptions and is computationally less cumbersome especially with a high number of parameters and with non linearities. Furthermore, Forni, Hallin, Lippi, and Reichlin (2004) and Stock and Watson (2002) show that principal components are consistent estimators of the common factors for large cross-sectional dimensions and sample size, and Stock and Watson (2009) argue that they are consistent even if there is some time variation in the loadings. We apply a standard normalization in the loadings so that $n^{-1}\boldsymbol{\lambda}^{\boldsymbol{x}\prime}\boldsymbol{\lambda}^{\boldsymbol{x}} = I$ and we compute $\boldsymbol{\lambda}^{\boldsymbol{x}} = \sqrt{n}\hat{\boldsymbol{Z}}$ and $\boldsymbol{f}_t^{\boldsymbol{x}} = n^{-1}\boldsymbol{x_t}\boldsymbol{\lambda}^{\boldsymbol{x}}$, where $\hat{\boldsymbol{Z}}$ are the eigenvectors corresponding to the k largest eigenvalues of $n^{-1}\boldsymbol{x}_t^{\prime}\boldsymbol{x_t}$, sorted in descending order.

Figure 1: Principal components



Note: This figure plots the first three principal content extracted from the information set.

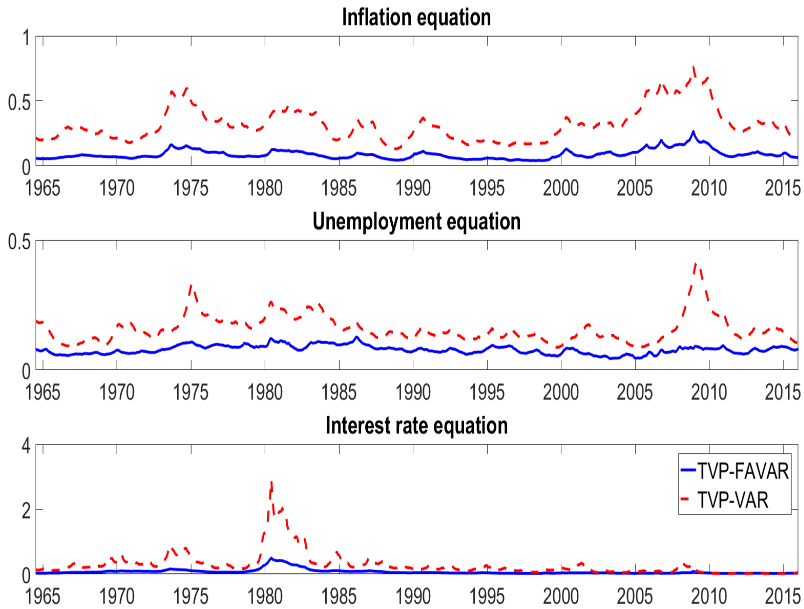
We estimate the first three principal components (k=3) from $\boldsymbol{x_t}$, which collects 122 macroeconomic and financial variables. The series are taken from the FRED-MD Monthly Database provided by the Federal Reserve Bank of St. Louis, which updates in real-time economic variables at monthly frequency.[7] There are eight groups of variables: 1) output and income, 2) labor market, 3) consumption and orders, 4) orders and inventories, 5) money and credit, 6) interest rate and exchange rates, 7) prices, 8) stock market. All the series are made stationary by applying the transformations reported in Appendix A. McCracken and Ng (2015) show that principal components extracted from this dataset have a prediction power similar to those extracted from the Stock-Watson dataset largely employed in previous macroeconomic studies of factor analysis. Giannone, Reichlin, and Sala (2006) and Stock and Watson (2002) provide evidence that two factors explain much of the predictable variation of the variables included in that dataset, while Bai and Ng (2007) and Stock and Watson (2005) estimate seven factors for the same Stock-Watson dataset. We consider the first three principal components in order to avoid the proliferation of parameters and explain enough variation in $\boldsymbol{x_t}$ (see Figure 1). McCracken and Ng (2015) find that the first three principal components estimated from the FRED-MD Monthly Database explain respectively 0.159, 0.069 and 0.066 of the variation in the data. Furthermore, they shows that these are associated with real economic activity (industrial production and employment), interest rate spreads and price. As pointed out by Bernanke, Boivin, and Eliasz (2005), including additional factors which are not informationally relevant renders the estimation less precise but the estimate remains unbiased.

In line with the literature on TVP models[8] we set the lag order to p=2. The matrices of parameters and hyperparameters $(\boldsymbol{B_t}, \boldsymbol{A_t}, \boldsymbol{H_t}, \boldsymbol{\Gamma}, \boldsymbol{\Xi}, \boldsymbol{\Psi})$ are estimated

[7] From the original dataset we eliminate series with several missing values.

[8] See Cogley and Sargent (2005), Primiceri (2005), Gambetti, Pappa, and Canova (2008), Benati (2008).

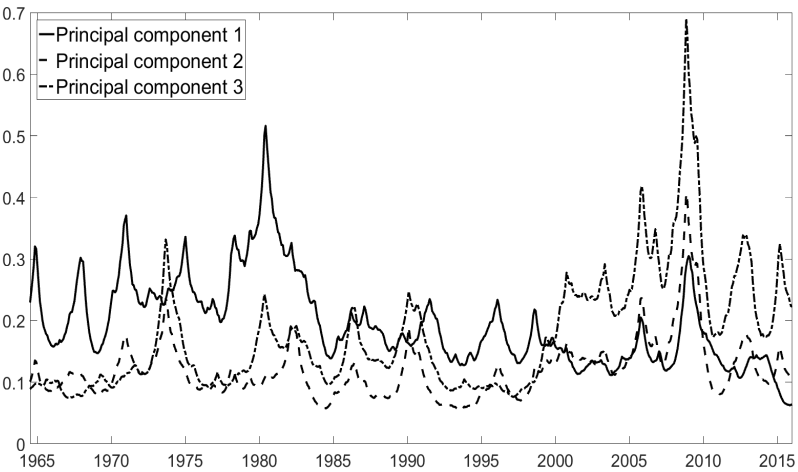
Figure 2: Time-varying volatilities of residuals in the equations of observed factors



Note: This figure plots the posterior mean of the standard deviation of residuals of equations for observed factors.

sequentially with a Gibbs sampling algorithm with the conditional prior and posterior distributions described in Appendix C. Figure 2 compares the time varying volatilities of residuals in the equations of observed factors in the TVP-FAVAR with the residuals from an analogous TVP-VAR without unobserved factors. Two findings stand out. First, in line with the previous literature we observe a drop in the volatilities after 1980, especially for residuals of the policy rate equation. Second, when the model incorporates unobserved factors the standard deviation of residuals reduces substantially, which suggests that the small-scale TVP-VAR used by Cogley and Sargent (2005) and Primiceri (2005) could suffer problems of omitted variables. This justifies the inclusion of unobserved factors in the model. Figure 3 shows the volatilities of residuals of the unobserved factor equations. The residuals associated with the first principal component exhibit a strong reduction in volatilities between 1980 and 2008, the period referred as to the Great Moderation. The residuals associated with the third principal component spike in 2009, capturing the large financial shock hitting the US economy.

Figure 3: Time-varying volatilities of errors in the equations of unobserved factors



Note: This figure plots the posterior mean of the standard deviation of residuals of equations for unobserved factors.

3 Structural analysis

3.1 Identification of Monetary Policy Shocks

Following Bernanke, Boivin, and Eliasz (2005) we identify only a monetary policy shock with recursive ordering, placing unobserved factors before observed factors. The main assumption is that unobserved factors do not respond to monetary policy innovations within a month. In order to achieve the identification of a monetary policy shock we divide two blocks of variables in $\boldsymbol{x_t}$: slow-moving and fast-moving. Slow-moving variables like output, employment and price indexes are assumed not to respond instantaneously to monetary policy shocks. In contrast, fast-moving variables like asset prices react to unanticipated changes in monetary policy within a period.[9] Appendix A provides a classification of the variables into the two categories.

In order to remove the direct dependence of principal components on Fed's policy instrument R_t, we first estimate the coefficient of R_t from the following regression

$$\hat{PC}_t = b_c \hat{PC}_t^s + b_r R_t + e_t \tag{7}$$

where $\hat{PC}_t^s$ are principal components extracted from the subset of slow-moving variables, which are a proxy for all the common components other than R_t. $\hat{\boldsymbol{f}}_{\boldsymbol{t}}^{\boldsymbol{x}}$ is constructed by subtracting $\hat{PC}_t - \hat{b}_r R_t$ in order to control for the part of $\hat{PC}_t$ that corresponds to the Federal Fund rate.[10]

3.2 Identification of Fiscal Policy Shocks

After having identified monetary policy shocks, we select episodes of exogenous shifts in fiscal policy using the narrative approach. We use the series of tax shocks and defense news shocks constructed respectively by Romer and Romer (2010) and Ramey (2011). One of the advantages of identifying a fiscal policy shock with the narrative approach is that this methodology avoids transforming the VAR into a moving average, reducing the problem of fiscal foresight. In particular,

[9] See also Christiano, Eichenbaum, and Evans (1999).

[10] An alternative identification approach is to extract distinct factors from the blocks of slow-moving and fast-moving variables. However, the first principal component of fast-moving variables turns out to be highly correlated with the Federal Fund rate, the coefficient of correlation being 0.973, and this would introduce collinearity to the system.

Ramey (2011) shows that professional forecasts Granger cause government spending shocks identified with a SVAR model, suggesting that they are anticipated by the private agents. By contrast, the defense news shocks of Ramey (2011) have fewer anticipation effects. Similarly, following the classification of Mertens and Ravn (2012) we consider only tax shocks which were not anticipated.

Furthermore, in order to make the impulse response functions estimated in different periods more comparable we apply the following criteria to select episodes of fiscal policy shocks: i) we consider only shocks taking place during phases of economic growth and not in recessions as defined by NBER; ii) we exclude fiscal policy shocks (either tax shocks or government spending shocks) that were counteracted by other fiscal policy shocks with the opposite sign; iii) we select only fiscal policy shocks that took place in a spell of time between 1984 and 2007, which is generally defined as the period of the Great Moderation. Figures 2 and 3 show that during this time the volatility of residuals dropped substantially, excluding the presence of large shocks in the US economy;[11] iv) Bilbiie, Meier, and Müller (2008) find a structural break in the transmission mechanism of a government spending shock after 1983 and Gerba and Hauzenberger (2013) find different government spending and tax multipliers during the Great Moderation compared with the period of the Volcker chairmanship; v) also, Melosi and Bianchi (2015) using a Markov Switching model show that during this period the fiscal policy regime was "passive", as a result our findings cannot be attributed to a mixture of changes in the fiscal policy stance.

[11] See also Primiceri (2005), Canova and Gambetti (2006), Gambetti, Pappa, and Canova (2008), Benati and Mumtaz (2007).

4 Results

We start by assessing the impact of a monetary policy shock in a FAVAR model with time invariant parameters. The model is the same one presented in Section 2, but with constant coefficients and volatilities, therefore it is analogous to Bernanke, Boivin, and Eliasz (2005), hereafter BBE (2005). The estimation is implemented with 10,000 iterations of the Gibbs sampling procedure, discarding the first 2,000 to minimize the effects of initial conditions.

Figure 4: Impulse responses of a monetary policy shock generated from a FAVAR

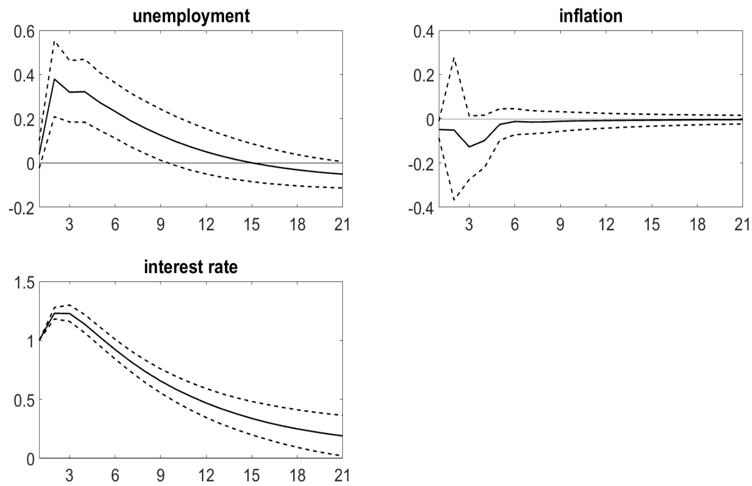
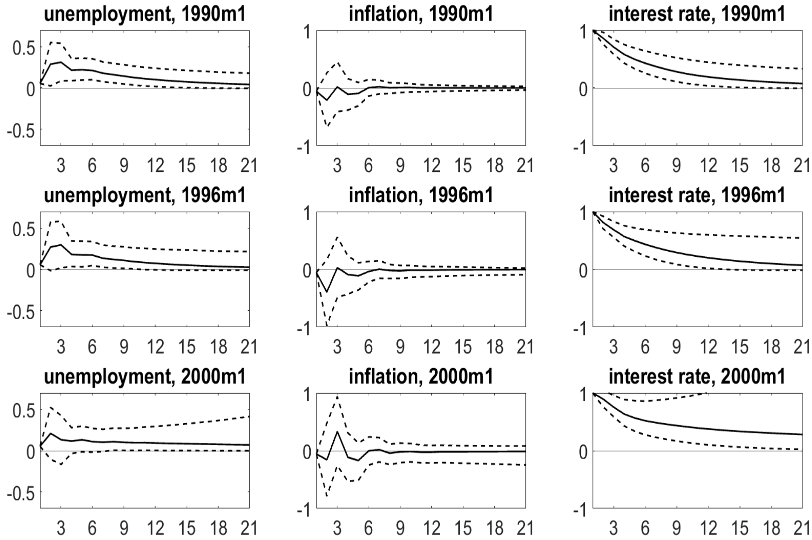


Figure 4 shows the responses of unemployment, inflation and federal fund rate to a negative monetary policy shock. The impact of monetary policy on unemployment is strong and persistent. A one-standard deviation shock leads to around 0.4% increase in unemployment. Qualitatively the response of unemployment is in line with the results of BBE (2005). The stronger response of unemployment in our study is in part due to the time sample. When we right censor the sample to 2001, as in BBE (2005), the increase in unemployment is more mitigated, less than 0.3% (see Figure 10 in the Appendix D). Furthermore, differently from their study, the reaction of inflation does not exhibit a "price puzzle", and declines to -0.1%, although on impact confidence bands are large.

Next, we estimate the effect of negative monetary policy shocks in the TVP-FAVAR model. It is important to assess whether different responses of monetary policy shocks are not due to changes in the conduct of monetary policy or in the structure of the economy. First, we find that the source of time variation derives from the variance of the residuals and not from the coefficients in line with Cogley and Sargent (2005), Primiceri (2005) and Koop and Korobilis (2010). In particular, the coefficients of the equation of the federal fund rate display very small time variation, suggesting that the systemic component of monetary policy was invariant during the sample. Second, we evaluate their impact in periods when the US economy does not register exogenous shifts in fiscal variables, that we define as "neutral" fiscal policy. Figure 5 compares the impulse responses of unemployment, inflation and interest rate in January 1990, January 1996 and January 2000. The pattern of the responses is similar across different periods and in line with the results of the FAVAR in Figure 4.

After having evaluated the overall performance of the FAVAR with time invariant and time varying parameters, we explore how the transmission mechanism of monetary policy shocks changes when combined with expansionary and contractionary fiscal policy shocks. As a benchmark, we consider the average of the impulse response functions estimated during each year in the spell of time from 1990 to 2005 in one period without fiscal policy shocks. In order to assess the role

Figure 5: Impulse responses of monetary policy shocks with neutral fiscal policy

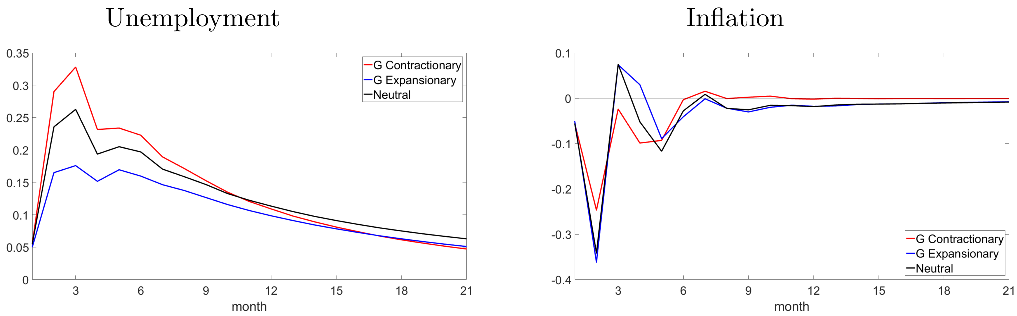


of fiscal policy in the transmission mechanism of monetary policy, we compute respectively the averages of the impulse response functions of monetary policy in periods with expansionary and contractionary government spending shocks and tax shocks weighted by the size of the fiscal intervention. Each impulse response function used to compute the averages is the median of 20,000 draws after having discarded the first 10,000 draws as burn-in.[12]

Figure 6 shows the impulse response of unemployment and inflation to monetary policy shocks combined with positive and negative government spending shocks. The difference is considerable: unemployment increases 0.2% more with contractionary government spending shocks than with expansionary government spending shocks. When we look at the reaction of inflation, we do not observe a

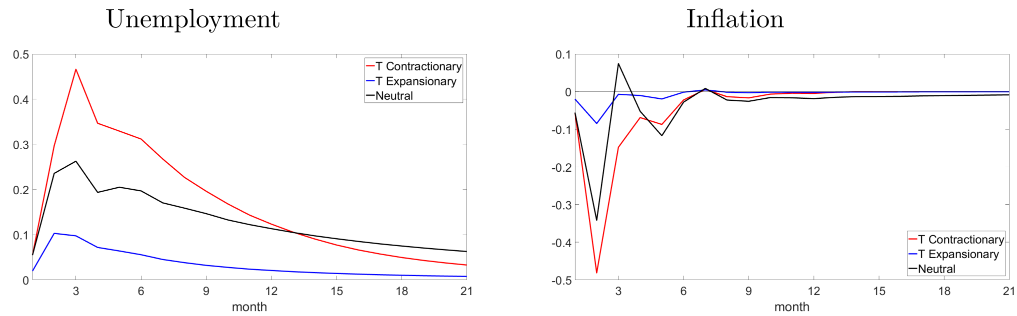
[12]The Appendix D reports individually the impulse response functions of monetary policy joint with expansionary and contractionary government spending and tax shocks.

Figure 6: Impulse response of unemployment and inflation to monetary policy shocks with government spending shocks



Note: The black line represents the average of impulse response functions of monetary policy shocks in periods with neutral fiscal policy. The red line and blue lines are the averages in periods with contractionary and expansionary government spending shocks weighted by the size of fiscal interventions.

Figure 7: Impulse response of unemployment and inflation to monetary policy shocks with tax shocks policy shocks



Note: The black line represents the average of impulse response functions of monetary policy shocks in periods with neutral fiscal policy. The red line and blue lines are the averages in periods with contractionary and expansionary tax shocks weighted by the size of fiscal interventions.

large divergence across different policy mixes.

Figure 7 compares the impulse response with positive and negative tax shocks. The difference is substantial both for unemployment and inflation. Unemployment rises by almost 0.5% following a monetary policy shock joint with a contractionary tax shock and only 0.1% with an expansionary tax shock. The same wedge is observed for inflation which falls to -0.5% with contractionary tax shock and to -0.1% with expansionary tax shocks. Overall these results suggest that fiscal policy shapes the response of unemployment to monetary policy shock through an aggregate demand channel that counteracts - in the case of expansionary fiscal policy - or amplifies - in the case of contractionary fiscal policy - the negative impact of monetary policy.

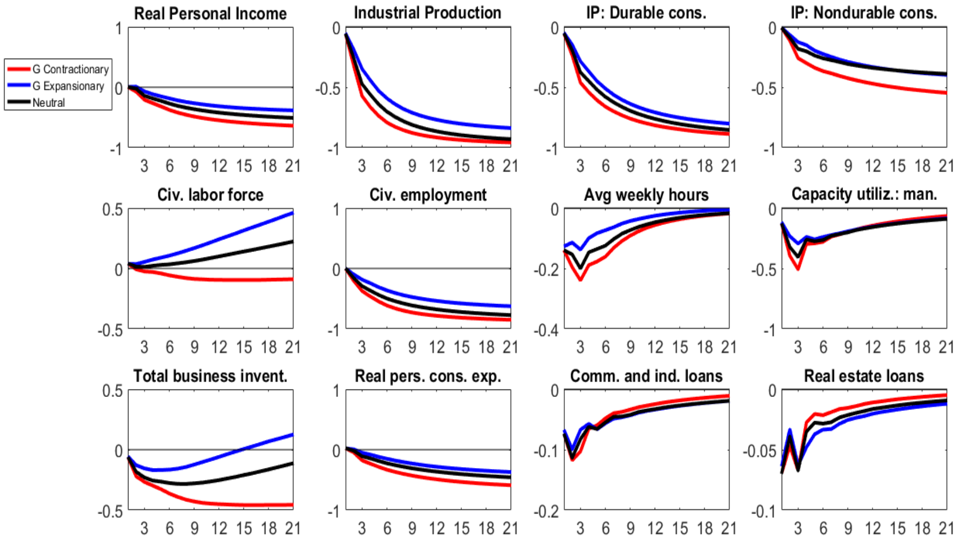
The results for the combination of monetary policy and tax shocks can be better understood through a textbook AS-AD model. A negative monetary policy shock corresponds to a shift of AD to the left, leading to a lower price level, lower economic activity and consequently higher unemployment. Fiscal policy shocks can move the AD curve either to the left or to the right. A contractionary tax shock results in a new equilibrium that intensifies the effect of the negative monetary policy shock. By contrast, an expansionary fiscal policy shock mitigates the effects of the monetary policy contraction.

4.1 Inspecting the transmission mechanism of monetary policy shocks

Figures 8 and 9 report the same impulse response functions as Figures 6 and 7 for some of the variables included in the information set, and they help to explain the different reactions of unemployment and inflation to monetary policy shocks combined with fiscal policy shocks.

Figure 8 shows that a contractionary monetary policy shock leads to a fall in real personal income, industrial production and real consumption expenditure, which is more pronounced when combined with contractionary than expansionary government spending shocks. The difference is particularly important for the industrial production of nondurable consumption goods and total business inventories and less evident for the industrial production of durable consumption goods

Figure 8: Impulse responses to monetary policy shocks joint with government expenditure shocks

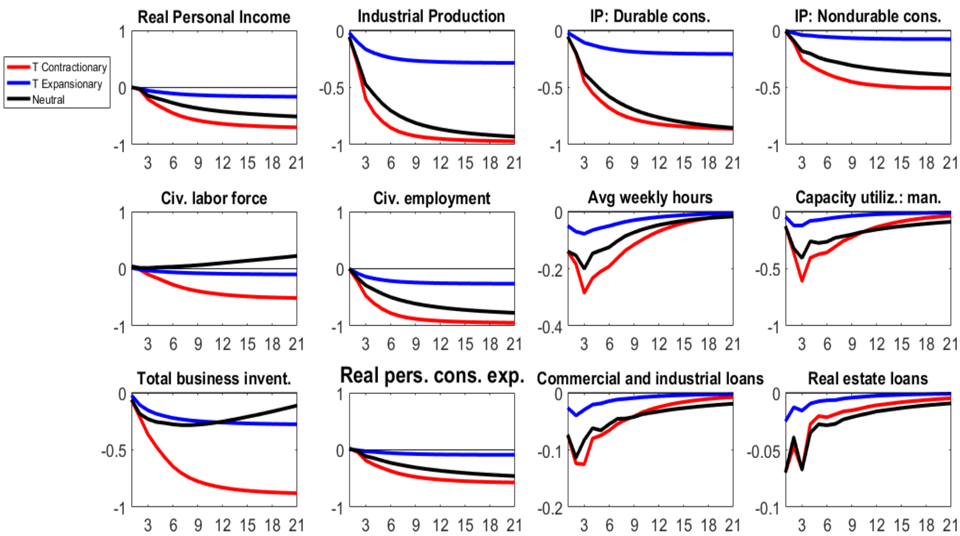


Note: The black lines represent the average of impulse response functions of monetary policy shocks in periods with neutral fiscal policy. The red line and blue lines are the averages in periods with contractionary and expansionary government spending shocks weighted by the size of fiscal interventions.

and capacity utilization in the manufacturing sector. In the credit market, loans (commercial and industrial loans) and mortgages (real estate loans) shrink following a tightening in monetary policy. The contraction of loans is more evident than mortgages, but the difference of the responses with expansionary and contractionary government spending shocks is more remarkable for mortgages. Concerning the labor market, fiscal policy shocks have a strong impact for both labor supply and labor demand. The reaction of the civilian labor force to monetary policy shocks is negative with contractionary government spending shocks and positive with expansionary government spending shocks. Also, civilian employment and average weekly hours decline more with contractionary fiscal policy.

Following a contractionary monetary policy shock labor demand and labor supply move in opposite directions. With sticky prices the variation in labor demand is larger than labor supply, hours and employment decline. A contractionary government spending shock pushes the labor demand further inwards and induces a strong negative impact on labor supply, resulting in a sizable reduction in employment and hours. On the other hand, an expansionary tax shock reduces the fall in labor demand caused by the monetary policy shock and boosts the labor supply. In the new equilibrium, hours and employment reduce less than in the case of no fiscal interaction.

Figure 9: Impulse responses to monetary policy shocks joint with tax shocks



Note: The black lines represent the average of impulse response functions of monetary policy shocks in periods with neutral fiscal policy. The red line and blue lines are the averages in periods with contractionary and expansionary tax shocks weighted by the size of fiscal interventions.

Figure 9 displays the responses of the same variables to negative monetary policy shocks combined with expansionary and contractionary tax shocks. Overall, we observe a similar reaction to the diverse policy mix but with some noticeable differences with respect to government spending shocks. Exogenous tax cuts reduce considerably the fall in industrial production and capacity utilization in the wake of a monetary policy shock. Furthermore, in the credit market expansionary tax shocks mitigate substantially the fall in both loans and mortgages by pushing aggregate demand. Finally, they have a stronger impact on labor demand than labor supply compared with positive government spending shocks. The civilian labor force does not increase, while civilian employment and average weekly hours reduce less.

Compared with a contractionary government spending shock, tax hikes contract labor demand more markedly and, to a lesser extent, labor supply also declines more, resulting in a deeper fall in hours and employment. Expansionary tax shocks reduce substantially the shift of labor demand and offset entirely the impact of the monetary policy shock on labor supply, as a result hours hardly change in equilibrium.

5 Conclusions

A strand of the empirical literature examines the evolution of the monetary policy transmission over time, applying econometric models with time varying parameters. This paper using a Time Varying Parameter Factor Augmented VAR model studies the interaction of fiscal and monetary policies in the U.S economy. The time varying structure of the model allows to simulate the impact of a monetary policy shock, identified with Structural VAR methods, in the same period of a fiscal policy shock, identified with the narrative approach. This procedure permits to analyze the effects of a combination of fiscal and monetary policy shocks on real and financial variables. A second contribution of this paper is that, by including unobservable factors in the model, it extends the impulse response analysis on several variables, which help understand the transmission mechanism of monetary policy changes conditional to fiscal policy.

The labor market plays a key role in explaining the heterogeneous response of the US economy to monetary policy shocks combined with different fiscal policy shocks. We find that the rise in unemployment following a contractionary monetary policy shock is dampened when combined with expansionary fiscal policy shocks, especially tax shocks. This is due mostly to a strong reaction of labor demand to tax shocks, while the response of labor supply is more mitigated, as predicted by models with sticky prices.

This study shows the importance of an indirect effect of monetary policy through labor demand as predicted by Heterogenous Agents New Keynesioan (HANK) models such as Kaplan, Moll, and Violante (2016). In this class of models, the presence of hand-to-mounth agents breaks down the Ricardian equivalence principle and monetary policy affects consumption mainly by increasing labor demand rather than through the intertemporal substitutions. In addition, a change in interest rate relaxes the government budget constraint, boosting aggregate demand and amplifying the impact of monetary policy on labor demand. In this paper we consider the exogenous component of fiscal policy that does not react to monetary policy, but we find a similar effect of fiscal policy that intensifies or dampens the impact of monetary policy through labor demand and the aggregate demand channel.

Our findings are also relevant for the current situation in the US where the tightening of monetary policy could be accompanied by expansionary fiscal policy in the form of an increase in public investment on infrastructures. According to our results, this policy mix could be successful in dampening the negative impact of the monetary policy on unemployment.

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Appendix A: Data

The dataset contains 122 macroeconomic and financial variables spanning from January 1973 to January 2012. All series are downloaded from St. Louis' FRED database. All variables are transformed to be approximate stationary. The transformation codes are: (1) no transformation; (2) Δx_t; (3) $\Delta^2 x_t$; (4) $log(x_t)$; (5) $\Delta log(x_t)$; (6) $\Delta^2 log(x_t)$ (7) $\Delta(\frac{x_t}{x_{t-1}} - 1.0)$. Slow $=$ 1 indicates that a variable is slow-moving, otherwise is a fast-moving variable. The fast-moving variables are interest rates, stock returns, exchange rates, monetary aggregates and loans. All variable descriptions and pneumonics are from the original source, except spreads.

Table 1: Information set

No.serie	Transformation	Mnemonic	Mnemonic	Description
1	5	1	RPI	Real Personal Income
2	5	1	W875RX1	Real personal income ex transfer receipts
3	5	0	DPCERA3M086SBEA	Real personal consumption expenditures
4	5	0	CMRMTSPLx	Real Manu. and Trade Industries Sales
5	5	0	RETAILx	Retail and Food Services Sales
6	5	1	INDPRO	IP Index
7	5	1	IPFPNSS	IP: Final Products and Nonindustrial Supplies
8	5	1	IPFINAL	IP: Final Products (Market Group)
9	5	1	IPCONGD	IP: Consumer Goods
10	5	1	IPDCONGD	IP: Durable Consumer Goods
11	5	1	IPNCONGD	IP: Nondurable Consumer Goods
12	5	1	IPBUSEQ	IP: Business Equipment
13	5	1	IPMAT	IP: Materials
14	5	1	IPDMAT	IP: Durable Materials
15	5	1	IPNMAT	IP: Nondurable Materials
16	5	1	IPMANSICS	IP: Manufacturing (SIC)
17	5	1	IPB51222S	IP: Residential Utilities
18	5	1	IPFUELS	IP: Fuels
19	2	1	CUMFNS	Capacity Utilization: Manufacturing
20	2	1	HWI	Help-Wanted Index for United States
21	2	1	HWIURATIO	Ratio of Help Wanted/No. Unemployed
22	5	1	CLF16OV	Civilian Labor Force
23	5	1	CE16OV	Civilian Employment
24	2	1	UNRATE	Civilian Unemployment Rate
25	2	1	UEMPMEAN	Average Duration of Unemployment (Weeks)
26	5	1	UEMPLT5	Civilians Unemployed - Less Than 5 Weeks
27	5	1	UEMP5TO14	Civilians Unemployed for 5-14 Weeks
28	5	1	UEMP15OV	Civilians Unemployed - 15 Weeks & Over
29	5	1	UEMP15T26	Civilians Unemployed for 15-26 Weeks
30	5	1	UEMP27OV	Civilians Unemployed for 27 Weeks and Over
31	5	1	CLAIMSx	Initial Claims
32	5	1	PAYEMS	All Employees: Total nonfarm
33	5	1	USGOOD	All Employees: Goods-Producing Industries
34	5	1	CES1021000001	All Employees: Mining and Logging: Mining
35	5	1	USCONS	All Employees: Construction
36	5	1	MANEMP	All Employees: Manufacturing
37	5	1	DMANEMP	All Employees: Durable goods
38	5	1	NDMANEMP	All Employees: Nondurable goods
39	5	1	SRVPRD	All Employees: Service-Providing Industries
40	5	1	USTPU	All Employees: Trade, Transportation & Utilities
41	5	1	USWTRADE	All Employees: Wholesale Trade
42	5	1	USTRADE	All Employees: Retail Trade
43	5	1	USFIRE	All Employees: Financial Activities
44	5	1	USGOVT	All Employees: Government
45	1	1	CES0600000007	Avg Weekly Hours : Goods-Producing

46	2	1	AWOTMAN	Avg Weekly Overtime Hours : Manufacturing
47	1	1	AWHMAN	Avg Weekly Hours : Manufacturing
48	4	1	HOUST	Housing Starts: Total New Privately Owned
49	4	1	HOUSTNE	Housing Starts, Northeast
50	4	1	HOUSTMW	Housing Starts, Midwest
51	4	1	HOUSTS	Housing Starts, South
52	4	1	HOUSTW	Housing Starts, West
53	4	1	PERMIT	New Private Housing Permits (SAAR)
54	4	1	PERMITNE	New Private Housing Permits, Northeast (SAAR)
55	4	1	PERMITMW	New Private Housing Permits, Midwest (SAAR)
56	4	1	PERMITS	New Private Housing Permits, South (SAAR)
57	4	1	PERMITW	New Private Housing Permits, West (SAAR)
58	5	0	AMDMNOx	New Orders for Durable Goods
59	5	0	BUSINVx	Total Business Inventories
60	2	0	ISRATIOx	Total Business: Inventories to Sales Ratio
61	6	0	M1SL	M1 Money Stock
62	6	0	M2SL	M2 Money Stock
63	5	0	M2REAL	Real M2 Money Stock
64	6	0	AMBSL	St. Louis Adjusted Monetary Base
65	6	0	TOTRESNS	Total Reserves of Depository Institutions
66	7	0	NONBORRES	Reserves Of Depository Institutions
67	6	0	BUSLOANS	Commercial and Industrial Loans
68	6	0	REALLN	Real Estate Loans at All Commercial Banks
69	6	0	NONREVSL	Total Nonrevolving Credit
70	2	0	CONSPI	Nonrevolving consumer credit to Personal Income
71	5	0	S&P 500	S&Ps Common Stock Price Index: Composite
72	5	0	S&P: indust	S&Ps Common Stock Price Index: Industrials
73	2	0	S&P div yield	S&Ps Composite Common Stock: Dividend Yield
74	5	0	S&P PE ratio	S&Ps Composite Common Stock: Price-Earnings Ratio
75	2	0	FEDFUNDS	Effective Federal Funds Rate
76	2	0	CP3Mx	3-Month AA Financial Commercial Paper Rate
77	2	0	TB3MS	3-Month Treasury Bill:
78	2	0	TB6MS	6-Month Treasury Bill:
79	2	0	GS1	1-Year Treasury Rate
80	2	0	GS5	5-Year Treasury Rate
81	2	0	GS10	10-Year Treasury Rate
82	2	0	AAA	Moodys Seasoned Aaa Corporate Bond Yield
83	2	0	BAA	Moodys Seasoned Baa Corporate Bond Yield
84	1	0	COMPAPFFx	3-Month Commercial Paper Minus FEDFUNDS
85	1	0	TB3SMFFM	3-Month Treasury C Minus FEDFUNDS
86	1	0	TB6SMFFM	6-Month Treasury C Minus FEDFUNDS
87	1	0	T1YFFM	1-Year Treasury C Minus FEDFUNDS
88	1	0	T5YFFM	5-Year Treasury C Minus FEDFUNDS
89	1	0	T10YFFM	10-Year Treasury C Minus FEDFUNDS
90	1	0	AAAFFM	Moodys Aaa Corporate Bond Minus FEDFUNDS
91	1	0	BAAFFM	Moodys Baa Corporate Bond Minus FEDFUNDS
92	5	0	EXSZUSx	Switzerland / U.S. Foreign Exchange Rate
93	5	0	EXJPUSx	Japan / U.S. Foreign Exchange Rate
94	5	0	EXUSUKx	U.S. / U.K. Foreign Exchange Rate
95	5	0	EXCAUSx	Canada / U.S. Foreign Exchange Rate
96	6	0	WPSFD49207	Producer Price Index by Commodity for Final Demand: Finished Goods
97	6	0	WPSFD49502	Producer Price Index by Commodity for Final Demand: Personal Consumption Goods
98	6	0	WPSID61	Producer Price Index by Commodity for Interm. Demand : Processed Goods for Intermediate Demand
99	6	0	WPSID62	Producer Price Index by Commodity for Interm. Demand : Unprocessed Goods for Intermediate Demand
100	6	1	OILPRICEx	Crude Oil, spliced WTI and Cushing
101	6	1	PPICMM	PPI: Metals and metal products:
102	6	1	CPIAUCSL	CPI : All Items
103	6	1	CPIAPPSL	CPI : Apparel
104	6	1	CPITRNSL	CPI : Transportation
105	6	1	CPIMEDSL	CPI : Medical Care
106	6	0	CUSR0000SAC	CPI : Commodities
107	6	0	CUUR0000SAD	CPI : Durables
108	6	0	CUSR0000SAS	CPI : Services
109	6	0	CPIULFSL	CPI : All Items Less Food
110	6	0	CUUR0000SA0L2	CPI : All items less shelter
111	6	0	CUSR0000SA0L5	CPI : All items less medical care
112	6	0	PCEPI	Personal Cons. Expend.: Chain Index
113	6	1	DDURRG3M086SBEA	Personal Cons. Exp: Durable goods
114	6	1	DNDGRG3M086SBEA	Personal Cons. Exp: Nondurable goods
115	6	1	DSERRG3M086SBEA	Personal Cons. Exp: Services
116	6	0	CES0600000008	Avg Hourly Earnings : Goods-Producing
117	6	0	CES2000000008	Avg Hourly Earnings : Construction
118	6	0	CES3000000008	Avg Hourly Earnings : Manufacturing
119	6	0	MZMSL	MZM Money Stock
120	6	0	DTCOLNVHFNM	Consumer Motor Vehicle Loans Outstanding
121	6	0	DTCTHFNM	Total Consumer Loans and Leases Outstanding
122	6	0	INVEST	Securities in Bank Credit at All Commercial Banks

Appendix B: Priors and Posteriors

Prior distributions and initial values

Equation (1) and (2) can be written in the following state-space form:

$$\tilde{x}_t = L f_t^x + u_t \tag{8}$$

$$y_t = \Phi(L) y_t + \nu_t \tag{9}$$

where $\tilde{x}_t = [x_t', f_t^{y'}]$ and $L = \begin{bmatrix} \Lambda^f & \Lambda^y \\ 0 & I \end{bmatrix}$ is a block matrix of factor loadings. The choice of the prior distributions follows Bernanke, Boivin, and Eliasz (2005) and Korobilis (2013) for the measurement equation and Primiceri (2005) for the state equation. In equation (8) an uninformative prior distribution is used for the matrix of loadings L and the inverse gamma distribution for the diagonal elements of Ω:

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

$\Omega_0 \sim G^{-1}(a_0\ ,\ b_0)$

where $a_0 = 0.01$ and $b_0 = 0.01$ denote the scale parameter and the shape parameter respectively. In equation (9) diffuse priors based on OLS estimations on the overall sample are used and initial states for all the parameters are independent. In particular, for B_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 H_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 Γ, Ξ and Ψ are assumed to be distributed as independent inverse-Wishart. Summarizing, the priors in the state equation take the following forms:

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

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

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

$\Gamma \sim W^{-1}(k_B^2 \cdot (1+n_B) \cdot V(\hat{B})\ ,\ 1+n_\Phi)$

$\Psi \sim W^{-1}(k_\alpha^2 \cdot (1+n_\alpha) \cdot V(\hat{I_n})\ ,\ 1+n_\alpha)$

$\Xi \sim W^{-1}(k_h^2 \cdot (1+n_h) \cdot V(\hat{A})\ ,\ 1+n_\sigma)$

where n_θ denotes the number of elements on each state vector $\theta = B, \alpha, h$; 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 (7) are sampled from the following Normal distribution:

$$L_i \sim N(L^*\ ,\ M^*)$$

where $L^* = M^* + \Omega_{i,i}^{-1} \cdot y' \cdot x_{i,t}$ and $M^* = (4I + \Omega_{i,i}^{-1} + y' \cdot y)^{-1}$. $\Omega_{i,i}$ denotes variance parameter in the prior on the coefficients of the i-th equation, L_i. 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 $\hat{\text{L}}$ and the residuals $\hat{\epsilon}$. The diagonal elements $\Omega_{i,i}$ are drawn from the following inverse gamma distribution:

$$\Omega_{i,i} \sim G^{-1}(a^* \ , \ b^*)$$

where $a^* = \frac{a_0}{2} + \frac{T}{2}$ and $b^* = \frac{b_0}{2} + \hat{\epsilon}_i{}'\hat{\epsilon}_i$. For equation (7) a Gibbs sampling procedure is applied drawing sequentially time varying coefficients (B_t), simultaneous relations (A_t), volatilities (H_t) and hyperparameters (Γ, Ξ, Ψ), conditional $\tilde{x}_t$ 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. In the first block B_t is drawn conditional on $\tilde{x}_t, A_t, H_t$ and hyperparameters. In the second block A_t is drawn conditional on $\tilde{x}_t, B_t, H_t$ and hyperparameters. In the third block H_t is drawn conditional on $\tilde{x}_t, B_t, A_t$, and hyperparameters. Finally, the hyperparameters Γ, Ψ and the diagonal blocks in Ξ are drawn from inverse-Wishart posterior distributions independent each other conditional on and y_t, B_t, A_t and H_t. In the first three blocks we reduce the problem into three state space linear and Gaussian forms and apply the Carter and Kohn (1996) algorithm.

Appendix C: 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:

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

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:

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

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:

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

Appendix D: Additional Figures

Figure 10: Impulse response function of a monetary policy shock in a FAVAR model (shorter time sample: Jan 1961 - Jun 2001)

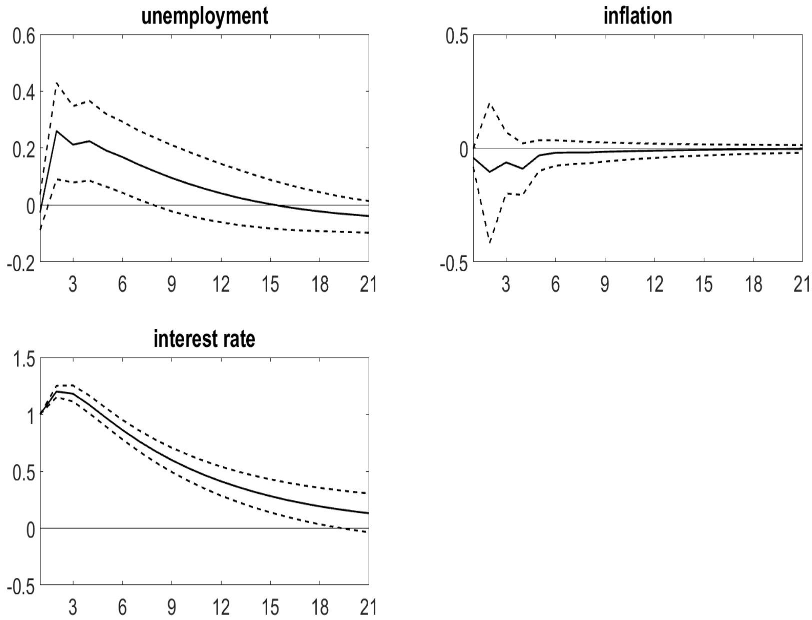
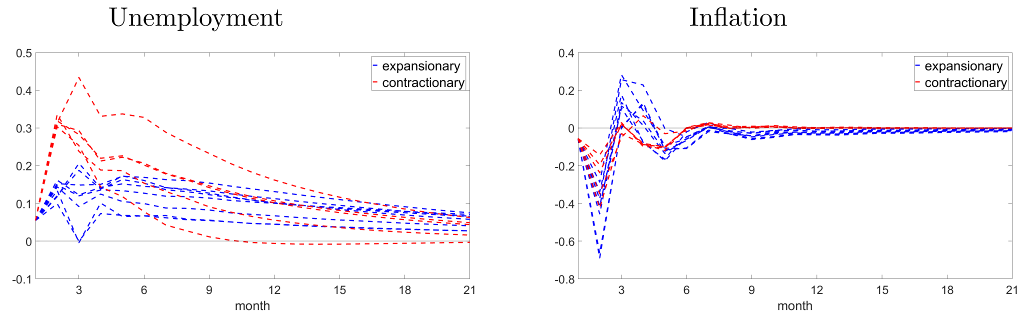


Figure 11: Impulse response of unemployment and inflation to monetary policy shocks with government spending shocks



Note: The dashed blue lines represent the impulse response functions of monetary policy shocks in periods with expansionary government spending shocks. The dashed red lines represent the impulse response functions of monetary policy shocks in periods with contractionary government spending shocks.

Figure 12: Impulse response of unemployment and inflation to monetary policy shocks with contractionary government spending shocks

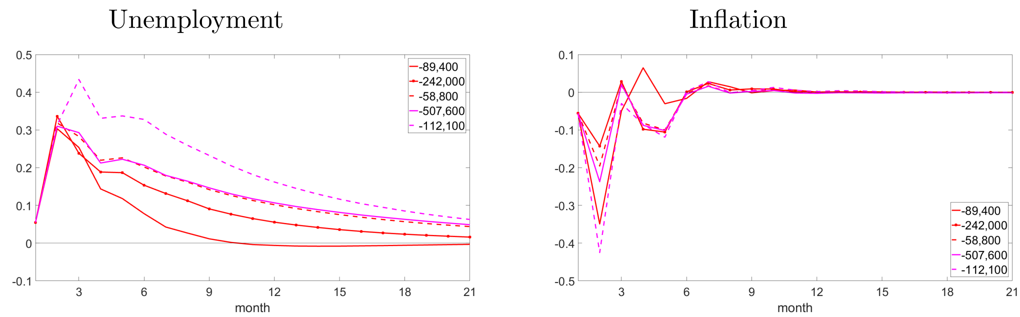


Figure 13: Impulse response of unemployment and inflation to monetary policy shocks with expansionary government spending shocks

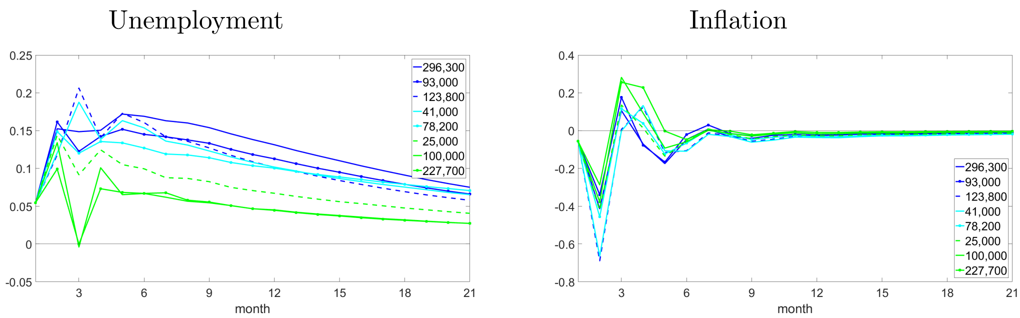
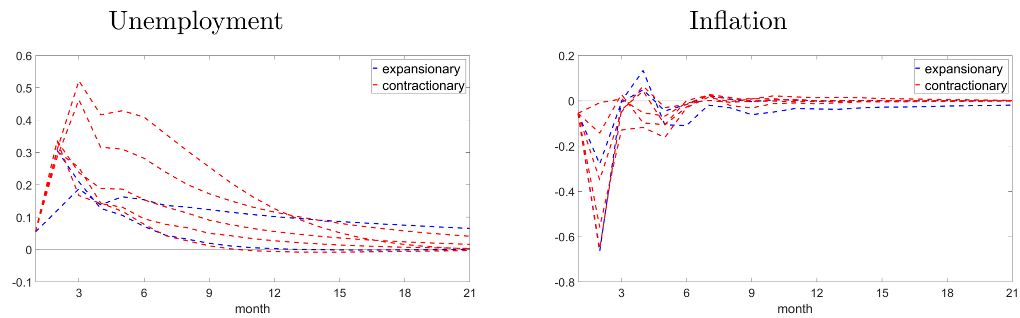


Figure 14: Impulse response of unemployment and inflation to monetary policy shocks with tax shocks



Note: The dashed blue lines represent the impulse response functions of monetary policy shocks in periods with expansionary tax shocks. The dashed red lines represent the impulse response functions of monetary policy shocks in periods with contractionary tax shocks.

Figure 15: Impulse response of unemployment and inflation to monetary policy shocks with contractionary tax shocks

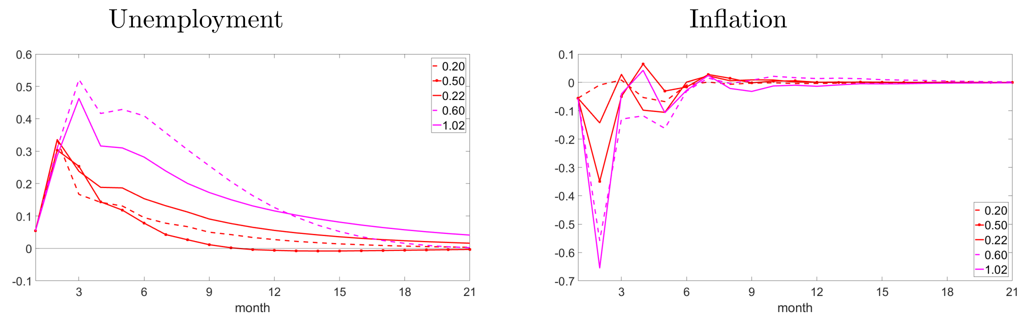


Figure 16: Impulse response of unemployment and inflation to monetary policy shocks with expansionary tax shocks