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# The Transmission Mechanism of Quantitative Easing: A Markov-Switching FAVAR Approach

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# The Transmission Mechanism of Quantitative Easing: A Markov-Switching FAVAR Approach

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This article assesses the impact of unconventional monetary policies and sheds light on their transmission mechanism in the United States. Using a three-variable Markov switching factor-augmented vector autoregression (MS-FAVAR) with time-varying transition probabilities and a shadow short-term interest rate, we allow our analysis to be free from arbitrary policy rate decisions and sample-splitting choices. By augmenting our informational set with variables able to grasp the functioning of Quantitative Easing, we can determine the differences between conventional and unconventional expansionary monetary policy shocks. Our results show a leading role for both the duration risk and the credit channels, a role for the default risk channel, and ultimately no evidence of the presence of a signaling channel during Quantitative Easing. We provide evidence that the large-scale asset purchase programs of the Federal Reserve effectively boosted the economy, mainly by modifying the term structure of the interest rates, thus providing strong economic stimulus throughout the financial sector.

*Keywords:* Monetary Policy; Financial Crisis; Structural analysis; Non-linear FAVAR.

*JEL Classification:* C54; E52; G01.

# 1 Introduction

The latest global financial crisis caused by the subprime housing bubble has required policymakers to revisit monetary policy actions, since the zero-lower bound (ZLB) in the short-term nominal interest rate was reached in November 2008, which until then was considered to be a highly unlikely event. The impossibility of lowering it further forced the Fed to implement unconventional policies, such as forward guidance and, most importantly, large scale asset purchases (LSAP), commonly referred to as Quantitative Easing (QE), which consists of increasing the balance sheet of the central bank by purchasing certain long-term assets to affect long-term returns. During the financial crisis, QE took place in the US in three different phases from December 2008 to October 2014, where the Fed purchased trillions of dollars in mortgage-backed securities, agency debt and Treasury Bills. Moreover, in 2011 the Fed did not affect its balance sheet in terms of size, but only in terms of average duration, by selling $400 billion bonds with shorter maturities to buy the same amount with longer maturities, an action known as Operational Twist (OT), hoping to influence the economy in the same way. Finally, in 2020, the Fed implemented another QE program to mitigate the economic slowdown caused by the COVID-19 pandemic.

As the short-rate nominal interest rate is the main policy instrument for central banks, the ZLB posed significant challenges when assessing the effectiveness of non-standard monetary policy measures through standard time series models. This was mainly due to the fact that the policy rate was close to zero for an extended period, but also due to a lack of agreement regarding the appropriate measure to use as a substitute. The literature on this topic is quite diverse. Wright (2012) and Baumeister and Benati (2010) studied QE policies by means of standard vector autoregressions (VAR) using a long-term interest rate as a policy rate, Krishnamurthy and Vissing-Jorgensen (2011) analyzed QE1 and QE2 in the US with an event study approach in a microeconometric framework, and most recently Inoue and Rossi (2019, 2020) departed from the usual macroeconometric setting by identifying a functional VAR model and extracting information from the whole term structure of the interest rate. As a matter of fact, the empirical identification of unconventional monetary policies poses significant challenges to policymakers and econometricians. Unlike conventional monetary policies, non-standard measures have been implemented by directly purchasing long-term bonds (mainly Treasury Bills, agency debt and mortgage-backed securities) while targeting no specific policy interest rate. Moreover, central banks put such purchases in place by relying on transmission mechanisms to the financial and real sectors that are not well standardized in the literature. However, some studies have analyzed the channels through which QE is expected to work in depth, including Joyce et al. (2012), who offer a detailed review of its main channels, Vayanos and Vila (2009) and Harrison (2012, 2017), who study the role of imperfect asset substitutability in New-Keynesian models, first portrayed by Tobin (1958, 1969), and Hohberger et al. (2019) and Mouabbi and Sahuc (2019), who estimate DSGE models in a ZLB environment. Most importantly, alternative empirical measures capable of capturing the full spectrum of unconventional monetary policies have been recently developed. One of the most promising instruments are the shadow interest rates, which are constructed by extrapolating information from shadow-rate term structure models (SRTSM), as in Wu and Xia (2016), Krippner (2013) and Lemke and Vladu (2017), or factor models, as in Lombardi and Zhu (2018). They correspond to the shortest maturity interest rate that the yield curve would have generated had the ZLB not been binding. Thus, shadow rates are allowed to reach negative values by extracting information on both monetary policy measures and market expectations regarding the evolution of different maturity interest rates.

This paper contributes to the literature by unravelling the transmission mechanisms underlying the functioning of unconventional monetary policies by using the shadow rate for the US economy developed by Wu and Xia (2016) within a Markov switching factor-augmented VAR (MS-FAVAR) with time-varying transition probabilities à la Huber and Fischer (2018). Moreover, the common informational set used in factor analyses is augmented with variables that are able to grasp the functioning of QE.

The econometric framework we adopt is particularly convenient for answering our research question for at least two reasons. First, it allows us to assess the effects of conventional and unconventional monetary policy implementations separately using a non-arbitrary long-term interest rate as a policy rate, i.e., via a shadow rate. Second, it does not bind the econometrician to split the dataset into pre- and post-ZLB periods, which could weaken the analysis in the presence of misspecified structural breaks.

Our results suggest a prominent role for the QE duration risk channel, which effectively narrows the yield curve on interest rates, and a jeopardized role for the default risk channel, acting on long-term corporate bonds. Furthermore, an expansionary unconventional monetary policy shock leads to four times better overall financial conditions, creating a higher degree of credit spread.

The remainder of this paper develops as follows: Section 2 describes the theoretical framework underlying the functioning of LSAP. Section 3 illustrates the empirical framework, identification and estimation. Section 4 describes the data and reports the results of the estimation. Section 5 provides robustness checks. Section 6 concludes. Data, detail estimation strategy and further robustness checks are reported in the Appendix.

## 2 Quantitative Easing and its transmission channels

The Federal Reserve has implemented unconventional policies since the very beginning of the last global financial crisis, by purchasing various types of long-term assets from the secondary market during three different rounds. QE1 started in December 2008 and lasted throughout March 2010 and involved the purchase of $1.5 trillion in bonds, including $1.2 trillion in US agency debt and mortgage-backed securities (hereafter MBS), and $300 billion in Treasury Bills. QE2 was announced in November 2010 and terminated in June 2012 and consisted in the purchase of a total of $827 billion in Treasury Bills. During the second program, $247 billion of US agency debt and MBS reached maturity. Finally, with QE3, which was announced and implemented in September 2012, the Fed bought $40 billion MBS and $45 billion in Treasury Bills per month until December 2013, when the committee agreed on initiating a tapering phase, by gradually lowering the acquisition of long-term bonds. The program officially ended in October 2014. Also, from September 2011 to December 2012, the Fed implemented the OT by buying $400 billion in Treasury Bills with a maturity of 6 to 30 years and by selling the same amount of Treasury Bills with a residual maturity of 3 years or less. The latter differs from the QE programs as it did not affect the size of the Fed's balance sheet, but rather its maturity composition, to accommodate financial conditions by putting downward pressure on longer-term bonds. Lastly, in the wake of the COV-SARS-2 world pandemic, the Fed announced a new QE program in March 2020, consisting of the purchase of more than $7 trillion in longer-term bonds. These measures are designed to provide stimulus when the economy is constrained by the ZLB on the nominal short-term interest rate. Recent years have left no doubt about their effectiveness, although a solid agreement upon the source of the latter is yet to be found. Many channels of transmission of QE have been identified during the last decade. Albeit their differentiation upon the variable of interest and the timing, market expectations have a crucial role in all their functioning, as announcements of new long-term asset purchases undoubtedly change agents' predictions about the future values of longer-term interest rates. This paper focuses on the four most widely spread channels in the literature, yet leaves space for new interpretations based on new findings.

The first transmission mechanism of QE that we consider is the *Duration Risk channel*. By purchasing a large quantity of high-maturity assets, a central bank inevitably affects the characteristics of the market. Particularly, by increasing the size of its balance sheet with long-term bonds, it decreases the quantity of available bonds of similar maturity in the market, thereby reducing the overall duration risk that the private sector must sustain. In turn, investors will be more likely to take the risk of purchasing such bonds, as they are perceived less risky, pushing their price up and causing their yield to decrease. As described in Vayanos and Vila (2009), the underlying assumption in support of this transmission mechanism is the existence of a fixed demand of certain types of assets in the market. This is determined by the presence of some preferred-habitat investors, in contrast to all the residual investors who are arbitrageurs ensuring the price vicinity of bonds with similar maturities. The former do not consider assets of different maturities as perfect substitutes and dislike heavy mutations in their portfolio position in terms of average maturity, while the latter become the marginal investors who price duration risk. When the monetary authority implements a LSAP policy, corresponding to a negative supply shock of longer-term maturity assets, the owners of the purchased assets will want to rebalance the average duration of their balance sheet by using their proceeds to purchase other long-term assets (that is why this transmission channel is also called a portfolio-rebalancing channel). The overall effect of the excess demand of longer-maturity assets will push their price up and their yield down. As households and firms are major owners of those assets, their overall wealth is going to increase, as well as their access to credit due to an increased value of collateral. This leads to higher consumption expenditure and investment and, in turn, overall higher output. The empirical evidence for this channel should emerge from a relatively stronger decrease in longer-term asset yields compared to shorter-term ones, provided that they carry the same risk.

Second, we focus on the *Default Risk channel*. If LSAP is effective in stimulating the economy, corporations should benefit from it due to a lower risk of their respective bonds in the market, which in turn should increase the value of their assets. Here, we harness the potential of QE to affect comparatively riskier sectors of the market. If this is the case, for the same maturity structure, the price of the bonds with higher default risk should rise in proportion to those with a lower risk of default. Evidence of this transmission mechanism can be found in corporate bonds with the same maturity, whose yield should be monotonically decreasing the greater the risk they carry.

Third, we consider the *Signaling channel*. Here, market expectations play a crucial role in the effectiveness of the LSAP implemented by the central bank. As with Forward Guidance, this channel is effective as long as the central bank's commitment to keeping its policy rate low is effective (Eggertsson et al., 2003). As outlined in Krishnamurthy and Vissing-Jorgensen (2011), a credible commitment can be achieved by the monetary authority in two ways: first, through explicit announcements by the central bank regarding the future of the policy rate, and second, when a large amount of long-term bonds is purchased, as if the central bank were to increase interest rates subsequently, it would incur losses. However, this last argument only holds if investors perceive the central bank to be a rational agent that internalizes these losses in their objective function. In terms of the empirical analysis, this channel should emerge from a comparatively higher impact on medium-term bonds relative to long-term bonds seen in a further reduction in the yield of the former. This is the case, as the central bank can only maintain its commitments until the economy recovers, which is likely to occur in the medium-term, when the price of the purchased assets will increase again, and they can be sold by the authority without incurring losses. Lastly, we examine the impact of LSAP through the *Credit channel*. As for conventional monetary policies, operating on the nominal short-term interest rate, QE mainly affects longer-term rates by increasing the value of their underlying assets, among which we find long-term investments to firms and mortgages granted to households by commercial banks. Therefore, as a result of a LSAP policy by the Fed, overall financial conditions should improve, thereby increasing loan volumes in turn. Thus, the effectiveness of this channel can be ascertained through a significant increase in loans to firms and households and from general indicators related to the health of the financial sector.

## 3 The econometric model: the Markov-switching FAVAR

To assess the effectiveness of the unconventional monetary policy and its transmission channels, we implement a MS-FAVAR with time-varying transition probabilities à la Huber and Fischer (2018). The model incorporates all the features of the original FAVAR developed by Bernanke et al. (2005), with the advantage of allowing the parameters to switch regimes, hence providing insights regarding the current stance of the monetary policy. Markov switching time-series models have been used to estimate parameter changes between economic expansions and recessions as in Huber and Fischer (2018), Billio et al. (2016) and Frühwirth-Schnatter (2001), between high and low inflation phases as in Amisano and Fagan (2013), or between different phases of conventional monetary policy as in Sims and Zha (2006). To our knowledge, this is the first factor model that allows for switches from a conventional to an unconventional monetary policy regime. The model is particularly suited for our economic research question for at least three reasons. First, it has the specific advantage of all factor-driven models of exploiting information from large macroeconomic datasets, narrowing the knowledge gap between the central banker and the econometrician, thus reducing the likelihood of price puzzles. Frequent issues of structural VARs, price puzzles occur if an estimated contractionary monetary policy shock drives up inflation, contrary to neoclassical macroeconomic theory. As interpreted by Sims (1992), this effect may not be a direct consequence of the decreased money supply, but rather reflect the choice of the policymaker to increase the policy rate in response to expected increasing inflation. The second advantage of the model lies in the possibility of computing impulse response functions on the whole system of variables constituting the informational set. This is a fundamental instrument to pull out relevant information about the transmission channels of both monetary policies. Third, by allowing endogenous regime switches, we let the model freely move from one regime to another. This avoids arbitrary splitting of the dataset into pre- and post-QE phases.

We start by introducing the original factor-augmented VAR model first developed by Bernanke et al. (2005) and then move to its Markov-switching specification. Consider a $K \times 1$ vector of unobserved factors $\boldsymbol{F}_t$, which capture latent information from a dataset, and an $M \times 1$ vector of observables $\boldsymbol{Y}_t$, whose joint dynamics is described by the following VAR equation:

$$\begin{bmatrix} \boldsymbol{F}_t \\ \boldsymbol{Y}_t \end{bmatrix} = \boldsymbol{\Phi}_1 \begin{bmatrix} \boldsymbol{F}_{t-1} \\ \boldsymbol{Y}_{t-1} \end{bmatrix} + \cdots + \boldsymbol{\Phi}_q \begin{bmatrix} \boldsymbol{F}_{t-q} \\ \boldsymbol{Y}_{t-q} \end{bmatrix} + \boldsymbol{u}_t, \tag{1}$$

where $[\boldsymbol{\Phi}_1', \ldots, \boldsymbol{\Phi}_q']$ is the vector of VAR coefficients and $\boldsymbol{u}_t$ is a zero-mean error term with variance-covariance matrix $\boldsymbol{\Sigma}_u$.

Let $\boldsymbol{X}_t$ be an $N \times 1$ vector of informational time series with $N \gg K + M$, linked to the factors and the observables by the following factor or observation equation:

$$\boldsymbol{X}_t = \boldsymbol{\Lambda}^y \boldsymbol{Y}_t + \boldsymbol{\Lambda}^f \boldsymbol{F}_t + \boldsymbol{e}_t, \tag{2}$$

where $\boldsymbol{\Lambda}^y$ and $\boldsymbol{\Lambda}^f$ are respectively $N \times M$ and $N \times K$ matrices of loadings and $\boldsymbol{e}_t$ is an $N \times 1$ normally distributed zero-mean uncorrelated vector of errors with diagonal variance-covariance matrix $\boldsymbol{\Sigma}_e = \begin{bmatrix} \varsigma_1{}^2 & 0 & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \varsigma_N{}^2 \end{bmatrix}$, with $\varsigma_i{}^2$ variances, for $i = 1, \dots, N$.

Equation (2) provides the intuition that both the observables $\boldsymbol{Y}_t$ and the factors $\boldsymbol{F}_t$ are common drivers of the dynamics of the informational set $\boldsymbol{X}_t$. The system (1)-(2) is what is called a factor-augmented vector autoregression (FAVAR).

Now consider the $R \times 1$ vector $\boldsymbol{z}_t = [\boldsymbol{F}'_t, \boldsymbol{Y}'_t]'$ with $R = K + M$. Suppose that the vector $\boldsymbol{z}_t$ follows a Markov-switching VAR, such that:

$$\boldsymbol{z}_t = \boldsymbol{a}_{S_t} + \boldsymbol{A}_{1,S_t}\boldsymbol{z}_{t-1} + \cdots + \boldsymbol{A}_{Q,S_t}\boldsymbol{z}_{t-Q} + \boldsymbol{\varepsilon}_t, \tag{3}$$

where $Q$ denotes the lag order, $\boldsymbol{a}_{S_t}$ is an $R$-dimensional intercept vector, $\boldsymbol{A}_{q,S_t}$ $(q = 1, \dots, Q)$ are $R \times R$ coefficient matrices and $\boldsymbol{\varepsilon}_t$ is a zero-mean normally distributed error term with $\boldsymbol{\Sigma}_{\varepsilon,S_t}$ variance-covariance matrix. The parameters $\boldsymbol{a}_{S_t}$, $\boldsymbol{A}_{q,S_t}$ and $\boldsymbol{\Sigma}_{\varepsilon,S_t}$ are allowed to change across regimes, where $S_t$ is assumed to be an unobserved binary Markov-switching variable marking the two alternative regimes of conventional ($S_t = 0$) or unconventional ($S_t = 1$) monetary policy. The matrix of transition probabilities is

$$\boldsymbol{P}_t = \begin{bmatrix} p_{11,t} & p_{12,t} \\ p_{21,t} & p_{22,t} \end{bmatrix}, \tag{4}$$

where $p_{ij,t} = Prob(S_t = j|S_{t-1} = i)$ with $\sum_{j=0}^{1} p_{ij,t} = 1$, $\forall i$ and $\forall t$. The subscript $t$ indicates the time-varying structure of the transition probabilities, in contrast to the literature which treats them as constant, e.g., Hamilton (1989). In this expression, the magnitude of the transition probabilities indicates the degree of persistence of the economy in one of the two regimes. For instance, the larger $p_{11,t}$ is, the higher the probability that the economy remains in a conventional monetary policy state.

In line with Huber and Fischer (2018), we adopt the early warning-Markov switching specification of Amisano and Fagan (2013) to model the time-variation in the transition probabilities:

$$p_{ij,t} = Prob(S_t = j|S_{t-1} = i, \boldsymbol{\zeta}_{t-1}) = \Phi(\gamma_{0,i} + \boldsymbol{\gamma}'\boldsymbol{\zeta}_{t-1}), \tag{5}$$

with

$$\Phi(\omega) = \int_{-\infty}^{\omega} \frac{1}{\sqrt{2\pi}} e^{-t^2/2}\, dt, \tag{6}$$

where $\gamma_{0,i}$ is a regime-specific intercept, and $\boldsymbol{\zeta}_{t-1}$ is a $J$-dimensional early warning indicator vector affecting the transition probabilities of the model, which includes variables useful in the statistical prediction of the regime switch of the monetary policy. In particular, the parameter vector $\boldsymbol{\gamma}$ measures how sensitive $p_{ij,t}$ is with respect to the corresponding element of the vector $\boldsymbol{\zeta}_{t-1}$. Following Amisano and Fagan (2013), in order to increase the efficiency of our estimates, we also impose a restriction on the slope coefficients of equation (5) so that they are equal across regimes, while regime-specific intercepts are kept in the specification. Note that equation (5) features similar characteristics to a standard probit model:

$$r_t = \gamma_{0,i} + \boldsymbol{\gamma}'\boldsymbol{\zeta}_{t-1} + \epsilon_t, \tag{7}$$

where $r_t$ is a real continuous latent variable and $\epsilon_t$ is a normally distributed error term with variance equal to unity. Equations (1)-(5) model the structure of a MS-FAVAR with time-varying transition probabilities.

Moving on to the estimation of the model, this can be done in two alternative ways, one of which is via a two-step procedure. The first step, as in Bernanke et al. (2005), consists of estimating the first $K+M$ principal components of $\boldsymbol{X}_t$ to obtain the space spanned by both the factors and the observables, and proceeds by extrapolating the estimated factors $\hat{\boldsymbol{F}}_t$ as the part of the estimated space not spanned by the vector of observables $\boldsymbol{Y}_t$. In the second step, the MS-VAR equation can be estimated either via the Expectation-Maximization (EM) algorithm as in Brooks et al. (2016), or with Bayesian techniques. This procedure is easy to implement and computationally feasible, but it has the disadvantage of estimating the MS-VAR equation in the observables and the factors treating the latter as known, which is not the case. Thus, we opt for an alternative way of estimating the system, that is with a one-step full Bayesian approach, as in Huber and Fischer (2018) (see Appendix B for details). We use Markov Chain Monte Carlo (MCMC) techniques, specifically the algorithm developed in Carter and Kohn (1994) where, conditional on the factors and the latent regimes, all the parameters in equation (3) can be successfully generated with Gibbs steps from the conditional density distributions of the parameters and eventually generated from the joint posterior distribution. Nevertheless, the actual sampling is carried out via random walk Metropolis-Hastings (RW-MH) steps due to the impossibility of using the Gibbs sampler under non-conjugate priors. The implementation of the MH steps is put forward by using the filter developed in Kim et al. (1999).

Finally, in order to properly estimate the MS-FAVAR, a set of identification restrictions must be imposed. The first one is specific to the one-step estimation method that we employ in order to account for the inclusion of the observables $\boldsymbol{Y}_t$ in the factor equation. To do so, a sufficient condition is to set the upper $K \times M$ block of $\boldsymbol{\Lambda}^y$ to zero and the upper $K \times K$ block of $\boldsymbol{\Lambda}^f$ to an identity matrix. A second restriction must be imposed to uniquely identify the likelihood function of the model, which otherwise would be invariant to permutations of the regimes. This issue is known as the label switching problem and is extensively discussed in Frühwirth-Schnatter (2006). To overcome this issue, we impose the restriction:

$$a_{j,S_t=0} > a_{j,S_t=1}. \tag{8}$$

Where $a_{j,S_t}$ corresponds to the intercept term of the $j$th equation that is related to the monetary policy instrument, i.e., the shadow-augmented federal funds rate. This implies that the conditional mean of the policy rate is lower during periods of unconventional monetary policy than during periods of conventional monetary policy. This assumption is consistent with the economic belief that the Fed is likely to implement unconventional policies once the ZLB on the interest rate is reached, and with the statistical estimation of the shadow rate by Wu and Xia (2016), which, contrary to the federal funds rate, is allowed to reach negative values whenever unconventional monetary policy actions are implemented and the economy hits the ZLB.

Third, we must impose an identification restriction to the structural form of equation (2), which we can write as:

$$\tilde{\boldsymbol{A}}_{0,S_t}\boldsymbol{z}_t = \sum_{q=1}^{Q} \tilde{\boldsymbol{A}}_{q,S_t}\boldsymbol{z}_{t-q} + \tilde{\boldsymbol{\varepsilon}}_{\boldsymbol{t}}, \tag{9}$$

where $\tilde{\boldsymbol{A}}_{0,S_t}$ is a $R \times R$ matrix of impact coefficients, $\tilde{\boldsymbol{A}}_{q,S_t}$ is the $R \times R$ matrix of lagged structural VAR coefficients and $\tilde{\boldsymbol{\varepsilon}}_{\boldsymbol{t}}$ is the vector of normally distributed structural error terms such that the reduced form error terms are $\boldsymbol{\varepsilon}_t = \tilde{\boldsymbol{A}}_{0,S_t}^{-1}\tilde{\boldsymbol{\varepsilon}}_{\boldsymbol{t}}$. We identify monetary policy in a recursive manner via a Cholesky ordering, by putting the shadow-augmented federal funds rate last. This procedure is standard in the literature and implies that the other observables and the factors of the MS-VAR equation are not allowed to respond to monetary policy shocks contemporaneously, but, in our specific case, are permitted after at least one month. Once these three identification restrictions are imposed, the model can be finally estimated.

# 4 Data and results

## 4.1 Dataset and the shadow rate

The empirical investigation is conducted using time-series data with monthly frequency spanning the period 1990:M1 - 2020:M2. The series are taken from the FRED-MD data set of McCracken and Ng (2016) of the Federal Reserve Bank of St. Louis, with the exception of all the US corporate bond yields, which are taken from the Thomson Reuters Datastream.

We have omitted the unconventional measures undertaken during the COVID-19 pandemic as they were still proceeding at the time of writing. The series are seasonally adjusted when applicable and properly transformed to induce stationarity. The informational matrix $\boldsymbol{X}_t$ consists of 101 diversified macroeconomic variables from different sides of the economy, such as consumer and producer price indices, employment, credit, Treasury Bills, corporate bond yields and spreads (see Appendix A for details). From this set of variables, it is assumed that relevant information about the whole state of the economy can be collected. The estimation is carried out simulating 50,000 draws, of which the first 20,000 are discarded, using two factors and two lags following the Bayes-Schwartz information criterion, but specifications with different lag orders are qualitatively similar. The prior specification follows Huber and Fischer (2018) (see Appendix B for details). We show the robustness in our results in Appendix C by using more diffuse prior specifications. The vector of observables is given by $\boldsymbol{Y}_t = [\boldsymbol{\pi}_t', \boldsymbol{u}_t', \boldsymbol{r}_t']$, where $\boldsymbol{\pi}_t$ is the consumer price index inflation rate, $\boldsymbol{u}_t$ is the unemployment rate and $\boldsymbol{r}_t$ is the monetary policy rate. We adapt our model to the Cholesky ordering of the time-varying parameter FAVAR of Korobilis (2013), hence assuming that unemployment and inflation cannot respond contemporaneously to a monetary policy shock, regardless of the latter being conventional or unconventional. Figure 1 shows that our monetary policy

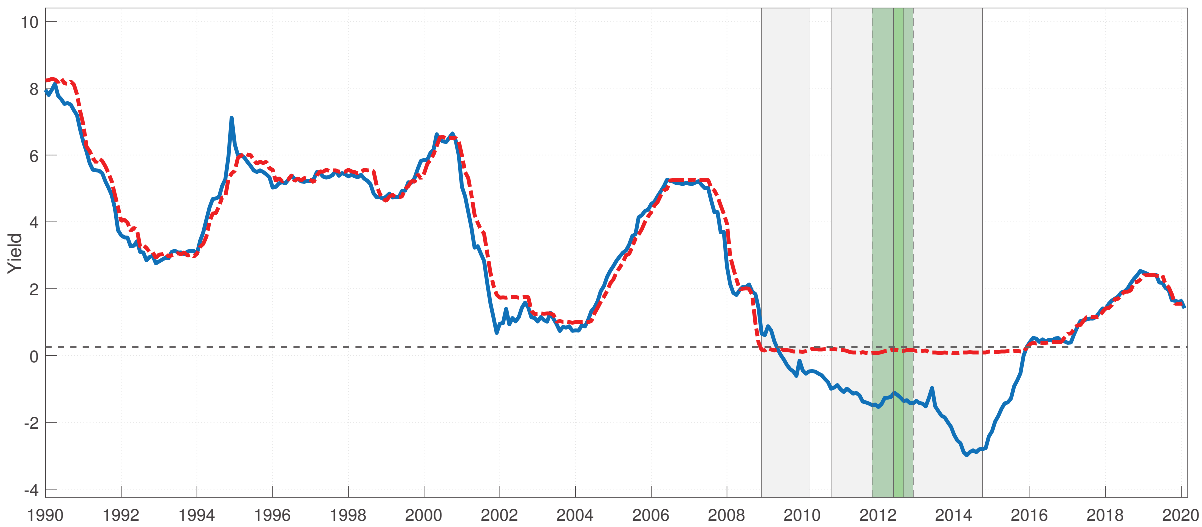


*Figure 1: Shadow Rate and Effective Federal Funds Rate. The dashed red line corresponds to the effective federal funds rate, while the solid blue line is the shadow rate estimated in the SRTSM in Wu and Xia (2016). The dashed black horizontal line is the lower bound $\underline{r}$. The gray areas and the light green area correspond to the periods of implementation of QE and OT respectively. The dark green areas are periods where QE and OT overlapped.*

rate $\boldsymbol{r}_t$ corresponds to the effective federal funds rate until 2008:M11, then from 2008:M12 to 2015:M11 it corresponds to the shadow rate developed in the SRTSM of Wu and Xia (2016) for the US economy, i.e., throughout the ZLB period, and then again to the effective federal funds rate until the end of the sample period. By construction, the short-term policy rate corresponds to the shortest maturity rate that the yield curve would generate, were the ZLB not binding. In particular, the short-term interest rate is:

$$\boldsymbol{r}_t = max(\underline{r}, \boldsymbol{s}_t), \tag{10}$$

where $\boldsymbol{s}_t$ is the shadow rate and $\underline{r}$ is a lower bound, here set to 0.25%, which is the lowest interest rate paid by the Fed just before the first QE program. If $\boldsymbol{s}_t > \underline{r}$, then the shadow rate is the effective federal funds rate. This procedure allows us to still use a short-term interest rate as a measure of the monetary policy as if the ZLB were not binding. As pointed out in Wu and Xia (2016), the slight difference between the two rates in Figure 1 reflects measurement error.

Regarding the choice of the policy rate, this paper differs from previous studies on the assessment of the unconventional monetary policy in at least two ways. Firstly, we do not use any discretionary long-term interest rates to simulate a QE shock, but we have chosen to augment the standard policy rate with a shadow rate, a measure that is able to collect all relevant information regarding the unconventional measures adopted by the Fed throughout the ZLB period. By doing so, we need not take any discretionary choice regarding the central banker's policy rate for QE, as we augment the instrument commonly used in the literature with a counterfactual of the nominal short-term interest rate, had it been allowed to pass over the ZLB. Secondly, using a shadow-augmented interest rate in a Markov-switching setup frees us from taking arbitrary sample-split decisions regarding the actual utilization of conventional or unconventional monetary policy instruments. By doing so, we can produce results that are comprehensive of both kinds of policy within a unique estimation exercise.

### 4.2 Synchronization and model accuracy

To trace the implementation of unconventional monetary policies, we analyze the time-varying transition probabilities for the whole sample. Figure 2 shows in red $Prob(S_t = 1|S_{t-1} = 0)$, i.e., the posterior mean of the probability of switching to an unconventional monetary policy in $t$ when being in a conventional monetary policy state in $t-1$, whereas the black line refers to $Prob(S_t = 0|S_{t-1} = 1)$ i.e., the opposite occurrence. As they are the off-diagonal elements of the transition probabilities matrix $\boldsymbol{P}_t$, the two probabilities always sum to one in each period of time, by construction.

The figure shows how the MS-FAVAR can track the QE periods and the OT, as the probability

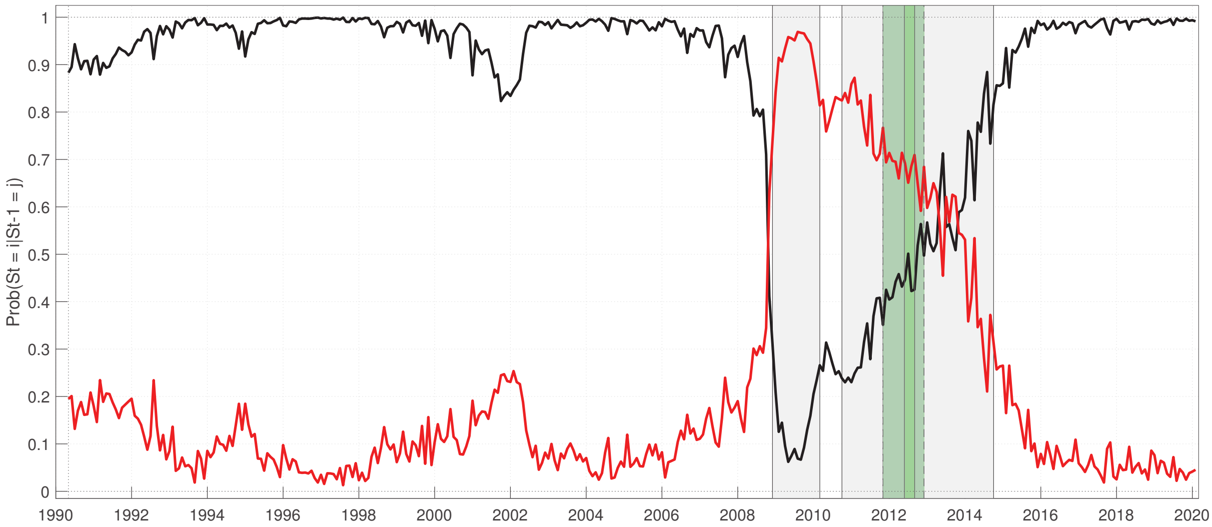


*Figure 2: Posterior mean of time-varying transition probabilities. The black line corresponds to* $Prob(S_t = 0|S_{t-1} = 1)$*; the red line corresponds to* $Prob(S_t = 1|S_{t-1} = 0)$*. The gray areas and the light green area correspond to the periods of implementation of Quantitative Easing (QE) and Operational Twist (OT) respectively. The dark green areas are periods where QE and OT overlap.*

of switching to an unconventional monetary policy regime was much higher from the end of 2008, corresponding to QE1, to the beginning of 2015. Note how, although the official end of QE3 is October 2014, the red line reaches the pre-crisis average values only around one year later. This result is likely to be driven by the shadow rate, which is negative by construction until the end of the ZLB period, officially corresponding to December 2015. To give a quantitative measure of the accuracy of the model, we compute the concordance statistic[1] (Harding and Pagan, 2002), constructed as:

$$CS = \frac{1}{T}\sum_{t=1}^{T}\left[(S_t \cdot \tilde{S}_t) + (1 - S_t)(1 - \tilde{S}_t)\right], \tag{11}$$

where $S_t$ for $t = 1, \dots, T$ is the regime indicator estimated by the model, and $\tilde{S}_t$ for $t = 1, \dots, T$ is a reference series, which we construct referring to actual implementations of unconventional monetary policies. Both series are dummy variable indicators equal to zero in

[1]First proposed in Harding and Pagan (2002), it is constructed in such a way that $CS \in [0, 1]$, where values equal to zero indicate that actual and estimated regimes are perfectly countercyclical, whereas values equal to unity mean perfect synchronization.

conventional monetary policy periods and equal to one otherwise. Our analysis leads to a value for the mean of the posterior distribution of the concordance measure equal to 0.90, indicating a remarkably high match between actual and estimated monetary policy regimes. These results support the utilization of such a model to investigate the differences between the transmission channels of conventional and unconventional monetary policies. Moreover, the capability of the model to match latent and actual states provides us with a powerful tool for researchers interested in out-of-sample predictions of unconventional monetary policy implementations.

### 4.3 The Markov-switching VAR equation

We now turn to the results of our analysis, specifically to the economic interpretation of the impulse response functions following an expansionary monetary policy shock in both regimes. Figure 3 shows the response of the three observables included in vector $\boldsymbol{Y}_t$, i.e., the inflation rate, the unemployment rate, and the shadow-augmented federal funds rate, which we use as monetary policy indicator. The first row refers to a standard expansionary monetary policy shock, which decreases inflation (depicting a canonical price puzzle) and significantly lowers the unemployment rate, albeit after approximately a couple of years. Its initial increase may be caused by a “real puzzle”, meaning that the model may be unable to fully capture the decision dynamics of the central banker who, expecting unemployment to rise, decides to lower the short-term interest rate. Unlike inflation, this puzzle lasts only for a small fraction of the whole impulse response horizon. After that, we can see the effectiveness of standard monetary policy measures in reducing unemployment. The second row refers to an expansionary unconventional monetary policy shock, and it shows significant differences from the previous result. Here the inflation rate increases for the first 12 periods and then slightly decreases until it reaches the steady state. The unemployment rate decreases on impact, reaching its maximum level after around one year from the implementation of the policy, which is about three times lower than the previous case. This shows a stronger impact of QE in alleviating more unfavorable labor market phases. The third row shows the difference between the posterior distribution of the impulse response functions of the two regimes for each variable, with their respective 68% confidence bands. If both bands are either above or below zero, it means that the possibility that there is no difference between the impulse responses of the two regimes is not rejected at that significance level. We can see that the difference is significant for all three variables, in particular for the unemployment rate and

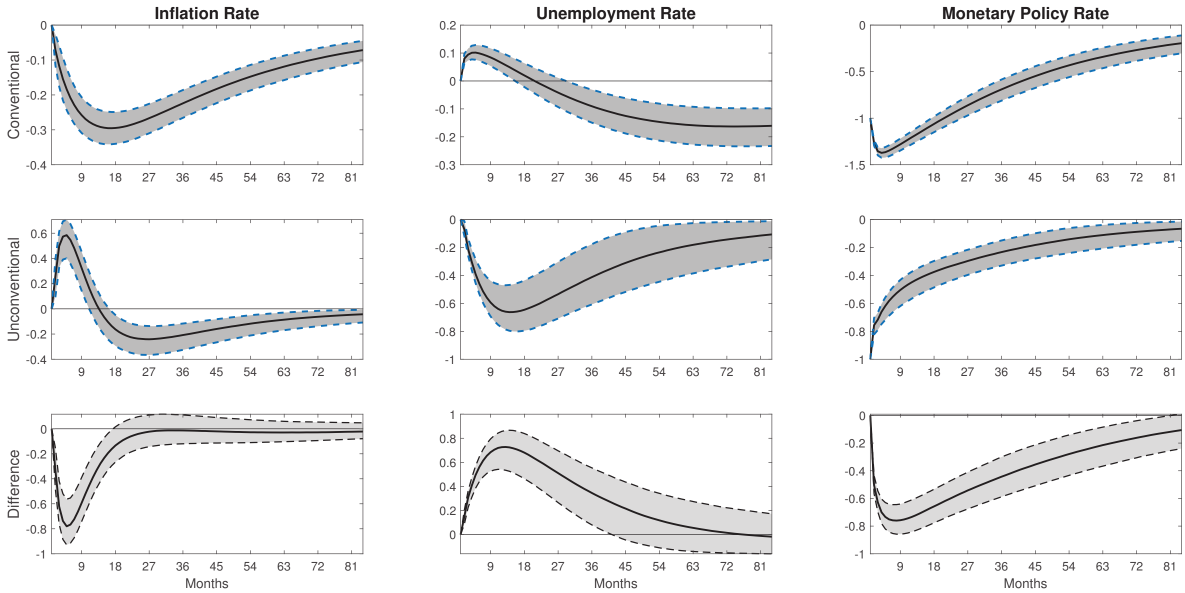


*Figure 3: Impulse response functions of the vector of observables $\boldsymbol{Y}_t$. The first row shows IRFs to an expansionary one standard deviation conventional monetary policy shock, the second row to an expansionary one standard deviation unconventional monetary policy shock, and the third row the difference between the posterior distribution of the IRFs for the two regimes. The black solid line is the median response, whereas the gray areas correspond to 68% confidence bounds.*

the policy rate, whose significance lasts the most.

Therefore, in both monetary policy regimes, an expansionary shock can stimulate economic recovery by decreasing the unemployment rate, albeit with different magnitudes.

## 4.4 Interest rates

As shown in the literature, VAR models suffer from the so called "curse of dimensionality", as parameter estimates become less reliable the higher the number of variables there are within the system. Therefore, to avoid this issue, the econometrician is forced to limit the number of endogenous variables to a reasonably narrow and arbitrary set. On the contrary, the FAVAR specification that we use allows us to investigate the transmission mechanism of the identified shocks on a large set of macroeconomic variables without any dimensionality issue. This allows us to have a bigger picture of both the responses and the interconnections of the whole economy, rather than just of an arbitrary chosen set of variables. Furthermore, the Markov-switching specification helps to disentangle the peculiarities of the conventional and the unconventional regimes. Thus, we inspect the behavior of selected variables in the informational set $\boldsymbol{X}_t$ from which the factors are extracted, followed by an expansionary monetary policy shock in both regimes.

Figures 4 and 5 show the response of a wide range of interest rates to a conventional and unconventional expansionary monetary policy shock. In both regimes the policy shock leads to a decline in the yields for both the government and the corporate sectors. However, there are some notable differences. The effect of QE appears to be lower in magnitude compared to a typical short-term interest rate reduction. With respect to the Treasury Bill responses in figure 4, the conventional monetary policy shock leads to an average decline on impact of around 100 base points (b.p.) for the entire maturity spectrum, while for the unconventional monetary policy scenario it is around 50 b.p. Also, notice how the degree of persistence is greater for the former. The difference in the posterior of the impulse response functions is significant, especially for short and medium-term maturities. With respect to the corporate

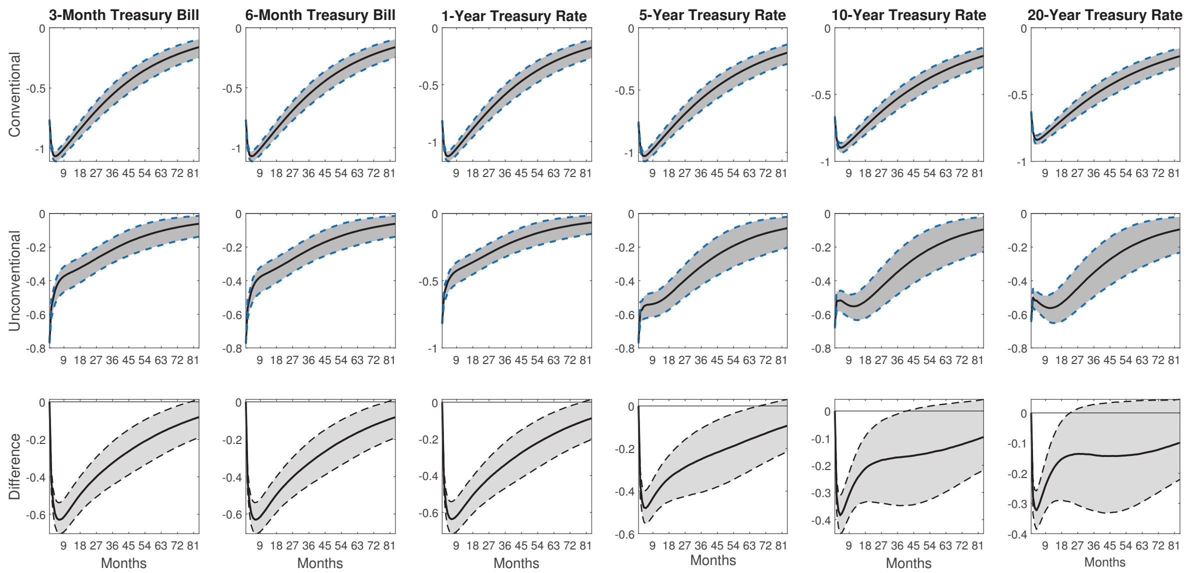


*Figure 4: Impulse response functions of Treasury Bills at different maturities. The first row shows IRFs to an expansionary one standard deviation conventional monetary policy shock, the second row to an expansionary one standard deviation unconventional monetary policy shock, and the third row the difference between the posterior distribution of the IRFs for the two regimes. The black solid line is the median response, whereas the gray areas correspond to 68% confidence bounds.*

bond market, we can see a similar pattern, namely a higher magnitude for the conventional regime, around 70 b.p. and a lower impact of the unconventional regime that is around 50 b.p., although we can see a less marked difference in terms of the persistence of the shock. The difference between the posteriors of the IRFs, shown in the last row of Figure 5, is significant only for the first 15 months after the shock, ruling out major differences in the long-term dynamics for the two regimes.

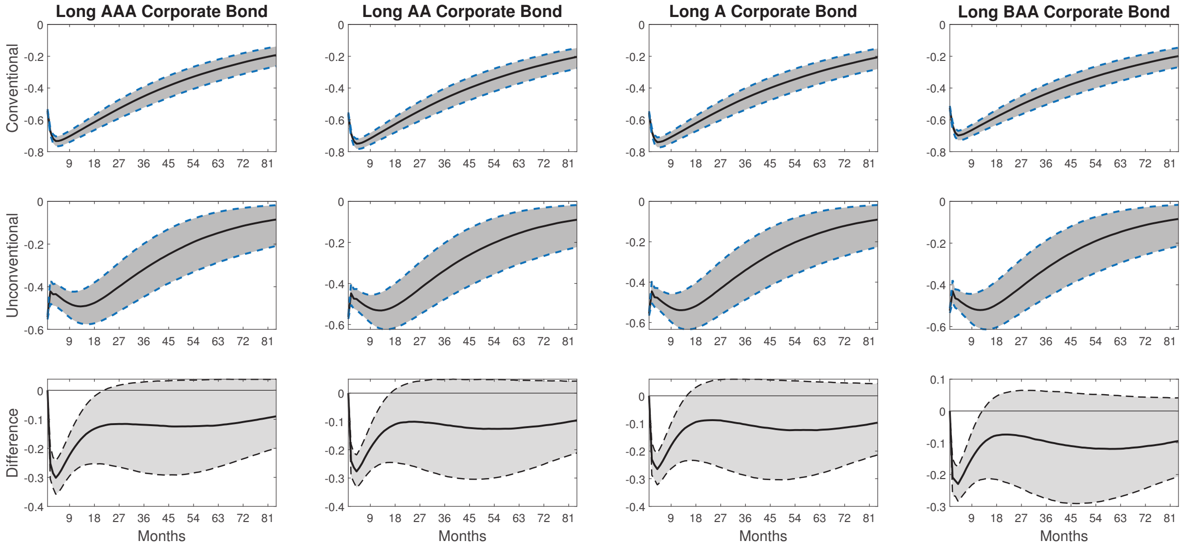


*Figure 5: Impulse response functions of long-term corporate bonds at different risk. The first row shows IRFs to an expansionary one standard deviation conventional monetary policy shock, the second row to an expansionary one standard deviation unconventional monetary policy shock, and the third row the difference between the posterior distribution of the IRFs for the two regimes. The black solid line is the median response, whereas the gray areas correspond to 68% confidence bounds.*

## 4.5 QE transmission channels

Decreasing interest rates, although informative regarding the stimulus provided by the central bank to the financial sector, do not shed light on the effectiveness of QE through its transmission channels. In this section we provide answers to those questions by examining the regime-specific effect of the monetary policy on a specific subset of $\boldsymbol{X}_t$. Most of the variables we analyze are augmented by the common informational set used in the factor models literature.

Figure 6 shows the IRFs of the spreads between the Treasury Bill rate – ranging from the three-month to the ten-year bond – and the effective federal funds rate. The first row of the figure refers to a standard monetary policy shock and shows increasing responses for all maturities except the one-year bond, decreasing in the short and the long-run. However, on average, a reduction in the short-term interest rate causes almost all Treasury Bills to fall relatively less than the policy instrument itself. Interestingly, the highest spread is found with the ten-year bond, about 22 b.p. on impact, consistent with the effect of expansionary conventional monetary policies in comparatively affecting more short-term interest rates. This effect is in line with the term spread response to the standard monetary policy shock of Fischer et al. (2019). The second row of the figure refers to an expansionary unconventional monetary policy shock. Three-month and six-month spreads increase significantly, although the increase is around 1 b.p. two years after the shock, showing no noticeable difference with the decrease of the effective federal funds rate. Conversely, one, five and ten-year spreads reach a significant maximum reduction of approximately 4, 16 and 24 b.p. respectively. This effect is consistent with the duration risk (portfolio-rebalancing) transmission channel of QE. Differences in the posterior distributions of the IRFs are all significant until the end of the chosen time horizon. Figure 6 shows evidence that the unconventional monetary policy is

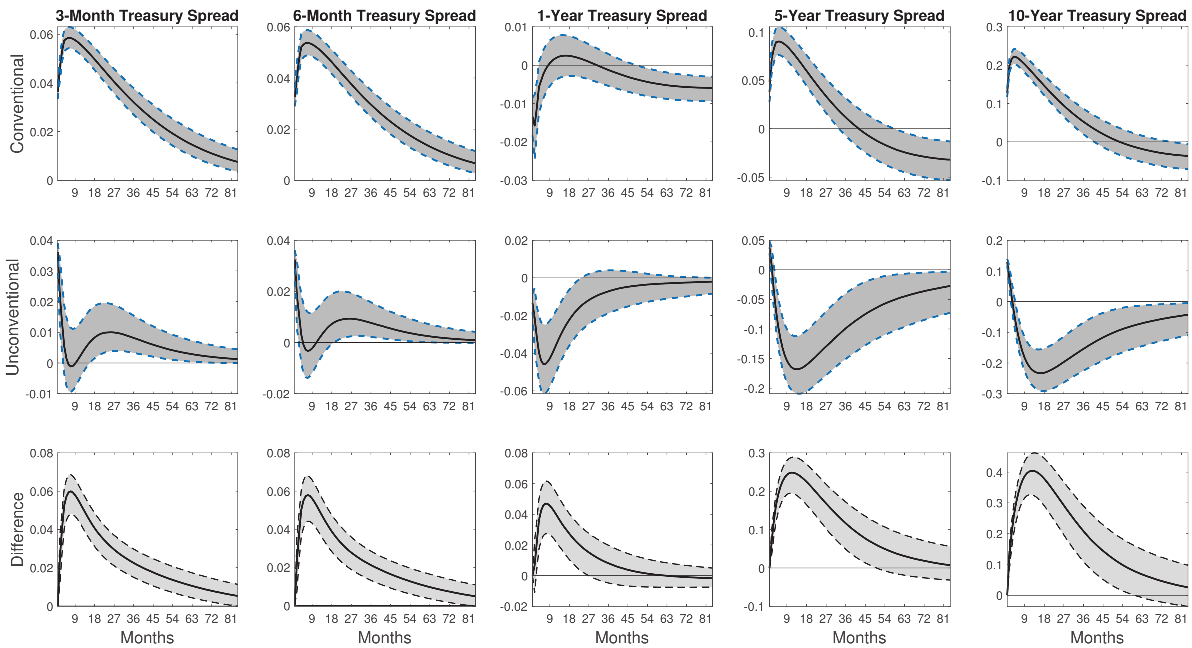


*Figure 6: Impulse response functions of Treasury Bill spreads. The first row shows IRFs to an expansionary one standard deviation conventional monetary policy shock, the second row to an expansionary one standard deviation unconventional monetary policy shock, and the third row the difference between the posterior distribution of the IRFs for the two regimes. The black solid line is the median response, whereas the gray areas correspond to 68% confidence bounds.*

more effective at reducing longer-term interest rates than short-term interest rates. According to Vayanos and Vila (2009), this highlights the role of preferred-habit investors who, in response to the central bank's LSAP, want to rebalance the average maturity of their portfolio and therefore invest in long-term bonds. This (re)purchase increases their price and decreases their respective yield. Furthermore, the spreads decrease monotonically, illustrating that the longer the maturity, the greater the impact of QE on the yield of those bonds. Note that the spread-variables that we use as proxies for the duration risk channel are robust to different specifications. In particular, if we use the spreads between the bonds and their closest one in terms of maturity, the results are qualitatively similar for both monetary policy shocks. The alternative specification would clearly show the monotonicity in the decreasing impact of QE on bonds. However, we decide to adhere to the literature, which commonly refers to spreads in the short-term policy rate i.e., the effective federal funds rate for the US economy.

To investigate the presence of the default-risk channel of QE, in Figure 7 we plot the IRFs of selected long-term corporate bond spreads for both regimes. We decide to use the interest rate differences of each bond to its closest safest counterpart. In our case, we have four long-term corporate bonds ranging from AAA to BAA degree of risk. Hence, we analyze the responses of the spread between the AA and AAA bonds, the A and AA, and finally the BAA to the A bonds. These spreads can be used as a proxy for the QE default risk transmission channel, as they allow us to assess whether the policy drives up the prices of the comparatively riskier bonds more than that of the less risky ones. Unlike the government bond market, here spreads respond differently both between regimes and across risk segments. The spread between AA and AAA corporate bonds decreases for both regimes, exhibiting the stronger impact of the shock on the riskier of the two in both cases. However, the impact for the unconventional regime reaches a maximum of 5 b.p., more than double the conventional regime, although it is less persistent. The spread between A and AA bonds is negative only for the QE shock, while positive otherwise. Finally, the spread between BAA and A bonds increases in both regimes, but to a lesser extent in the unconventional monetary policy regime, reaching a maximum of 2.5 b.p. against the 4.5 b.p. of the conventional regime. The third row of Figure 7, showing the difference between the posterior of the IRFs, is more significant for the riskier segment of the market. Therefore, albeit a diverse behavior from a quantitative perspective, the most relevant qualitative difference lies in the medium-high segment of the corporate bond market, namely the A-rated bonds. Thus, we only find partial evidence of the default-risk channel, which theoretically should monotonically lower interest rates on riskier bonds, and which here predominantly impacts the medium-high risk segment of the corporate bond market.

Moving on to the signaling channel of QE, this transmission mechanism is based on the cred-

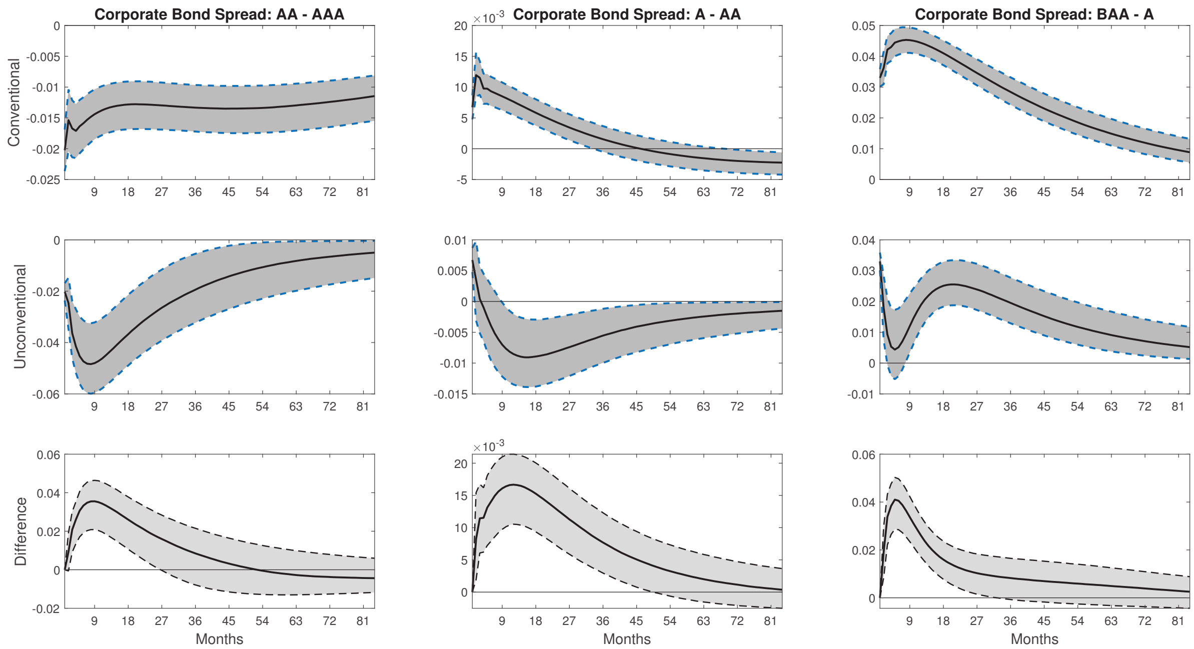


*Figure 7: Impulse response functions of corporate bond spread. The first row shows IRFs to an expansionary one standard deviation conventional monetary policy shock, the second row to an expansionary one standard deviation unconventional monetary policy shock, and the third row the difference between the posterior distribution of the IRFs for the two regimes. The black solid line is the median response, whereas the gray areas correspond to 68% confidence bounds.*

ibility of the central bank's commitments to keep the policy rate low for an extended period. This channel is effective if LSAP has a greater impact on medium-term bonds, as it relies on the assumption that the central bank can only maintain its commitment until economic recovery is achieved. The first panel of Figure 8 shows the difference between the posterior distributions of the IRF for the five-year and the twenty-year Treasury Bill after an expansionary unconventional monetary policy shock. Following Krishnamurthy and Vissing-Jorgensen (2011), we take the five-year bond as proxy for a medium-term asset. The response is negative and significant for the first six months, meaning that medium-term yields decrease more in proportion to long-term ones, but subsequently a significant increase begins until convergence to the steady state is reached. This illustrates merely a marginal and short-lived impact of the signaling channel, once again highlighting a leading role for the duration risk channel. In fact, after the initial response, 20-year yields decrease significantly compared to the 5-year bill yields. Furthermore, the second and third panels of Figure 8 support this claim by displaying decreasing posterior differences between the 5-year and the 3-month bill and between the

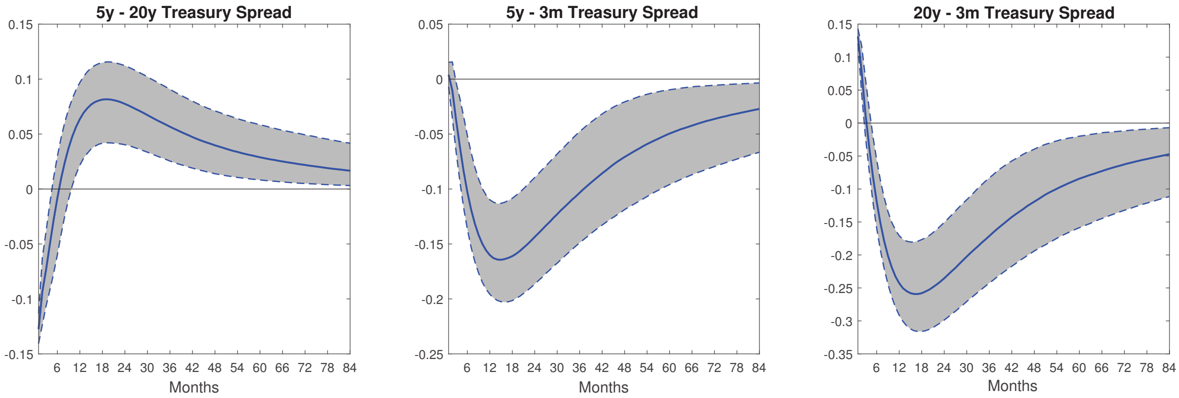


*Figure 8: Signaling channel. Differences in the posterior distribution of impulse response functions for selected Treasury Bill yields to an expansionary one standard deviation unconventional monetary policy shock. The blue solid line is the median response, whereas the gray areas correspond to 68% confidence bounds.*

20-year and the 3-month bill respectively. Medium and long-term yields decline more than the shorter-term yields, again exhibiting the monotonically decreasing behavior in the interest rate shown in Figure 6.

Lastly, in order to ascertain the effectiveness of LSAP in improving the financial market via the credit channel of QE, we adopt two of the Chicago Fed's National Financial Condition Indices, specifically the general one and the risk sub-index. The first indicates U.S. financial conditions in money markets, debt and equity markets, the second captures volatility and funding risk. The series are built such that higher (lower) values are associated with tighter (looser) financial conditions, while a value equal to zero indicates average financial conditions. Figure 9 shows the effect of an expansionary monetary policy shock for both regimes. The impulse responses are similar for the two indices, but different across regimes. First, note that they decrease for both states, which shows that both monetary policy measures can improve the ability of financial institutions to make loans and reduce funding risk and financial market volatility. However, QE exerts a stronger impact, four times greater, as both indices reach a maximum decrease of around 0.06, versus the 0.015 of the conventional regime. This shows evidence of the presence of a stronger ability of LSAP to positively affect the financial system compared to a conventional decrease of the short-term nominal interest rate.

## 4.6 Other responses and additional results

As illustrated above, one of the advantages of the FAVAR specification lies in the possibility of digging into the effect of the shock identified in the VAR equation across the whole

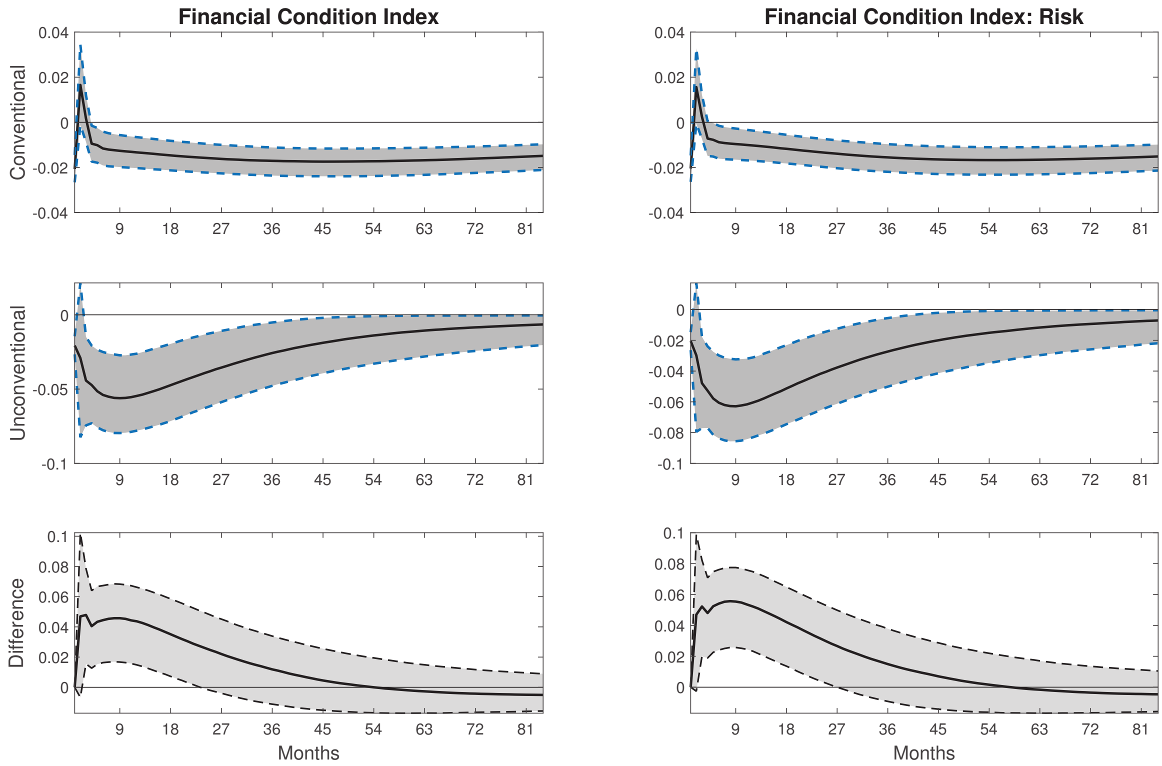


*Figure 9: Impulse responses of national financial condition indices for the United States. The first row shows IRFs to an expansionary one standard deviation conventional monetary policy shock, the second row to an expansionary one standard deviation unconventional monetary policy shock, and the third row the difference between the posterior distribution of the IRFs for the two regimes. The black solid line is the median response, whereas the gray areas correspond to 68% confidence bounds.*

informational set. Figure 10 shows how monetary policy affects an additional set of selected variables. Regarding money aggregates, both regimes exert a similar effect on M2, while for M1 a high and significant impact is exerted only by the conventional monetary policy regime. This may indicate a greater role for standard measures in increasing the amount of circulating currency and overnight deposits. In fact, it is reasonable to think that, since QE has a stronger effect on the longer end of the yield curve, its effect should be more present on money aggregates that comprise higher maturity deposits. It can also be seen that business loans increase in both regimes, albeit in greater magnitude in the unconventional monetary policy regime, therefore, we can confirm a prominent role in the financial sector for QE with respect to standard monetary policy measures. These last results are consistent with the effect of the financial condition indices shown in Figure 9. Finally, exchange rates follow very similar patterns in both regimes, as shown by the low significance of the difference in the posteriors of their IRFs. Consistently with Inoue and Rossi (2019), this does not suggest any particular role of QE in influencing the exchange rates with respect to standard monetary policy measures, as both result in a depreciation of the US dollar against the foreign currency.

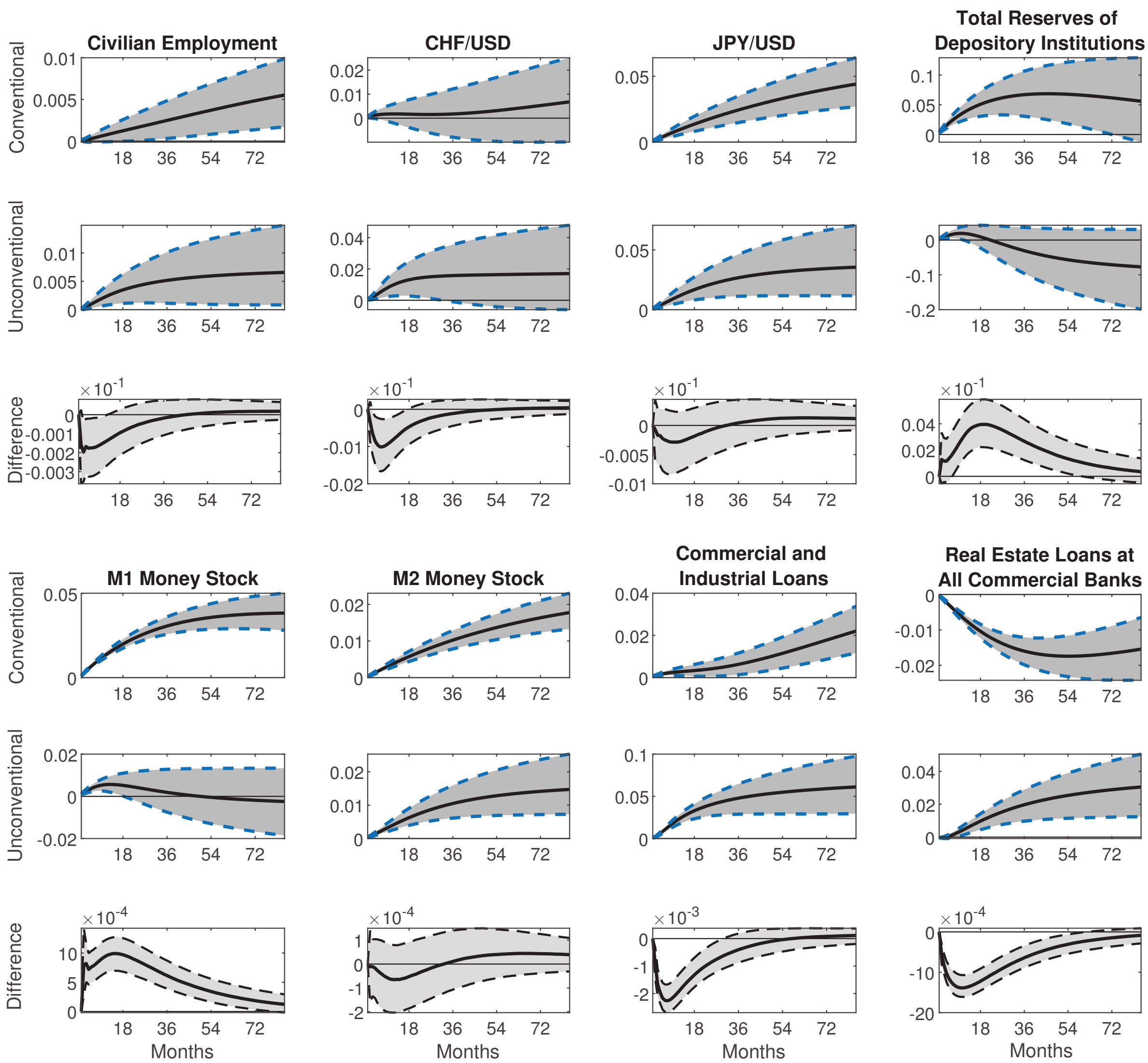


*Figure 10: Impulse responses of other selected variables. The first and fourth row show IRFs to an expansionary one standard deviation conventional monetary policy shock, the second and fifth row to an expansionary one standard deviation unconventional monetary policy shock, and the third and last row the difference between the posterior distribution of the IRFs for the two regimes. The black solid lines are median responses, while the gray areas correspond to 68% confidence bounds.*

Another typical exercise of the VAR literature consists in calculating the forecast error variance decomposition (FEVD), i.e., the fraction of the forecast error that can be attributed to the shock related to each variable of the system. As shown in Bernanke et al. (2005), the analysis can be carried out in a FAVAR context as well, by extracting relevant information from the moving average representation and the structural shocks of the VAR. Furthermore, the two-regime MS-FAVAR specification, by returning two sets of impulse response functions, allows us to investigate the differences between the fraction of variance explained by a conventional and an unconventional monetary policy. Table 1 shows the fraction of the forecast error attributable to the monetary policy shock in both regimes, as well as the $R^2$ of the common component, computed by regressing $\boldsymbol{z}_t$ against each variable of the informational set $\boldsymbol{X}_t$ and each observable variable $\boldsymbol{Y}_t$, individually. The first panel shows results for the observables of the MS-VAR equation, for which it is evident that the monetary policy shock plays a prominent role in explaining the variance of the shadow-augmented federal funds rate in both regimes. Concerning unemployment and inflation rates, it seems that the conventional monetary policy shock accounts for a larger amount of their variance, compared to the unconventional case. The second panel refers to the variables of the informational set. Here we calculate FEVD averages computed by grouping the contribution of both shocks by macro clusters according to the FRED classification (see Appendix A for details).

Forecast Error Variance Decomposition and $R^2$ of the common component

| **Variables** | $\boldsymbol{FEVD_{S_t=0}}$ | $\boldsymbol{FEVD_{S_t=1}}$ | $\boldsymbol{R^2}$ |
|---|---|---|---|
| Shadow-augmented Effective Federal Funds Rate | 0.99 | 0.99 | *1.00 |
| Unemployment Rate | 0.25 | 0.21 | *1.00 |
| CPI Inflation Rate | 0.07 | $0.06 \times 10^{-2}$ | *1.00 |
| Output and Income | 0.15 | 0.09 | 0.04 |
| Labor Market | 0.53 | 0.49 | 0.15 |
| Housing | $3.49 \times 10^{-5}$ | $4.21 \times 10^{-5}$ | 0.54 |
| Consumption, Orders and Inventories | 0.01 | 0.07 | 0.05 |
| Money, Credit and Financial Condition Indices | 0.01 | 0.10 | 0.11 |
| Interest Rates and Spreads | 0.08 | 0.12 | 0.54 |
| Exchange Rates | 0.88 | 0.54 | 0.01 |
| Prices | 0.01 | 0.01 | 0.01 |
| Stock Market | $2.28 \times 10^{-7}$ | $6.11 \times 10^{-8}$ | 0.006 |

*Table 1: The columns $FEVD_{S_t=0}$ and $FEVD_{S_t=1}$ report the fraction of the variance of the forecast error at the 82-month horizon explained respectively by a conventional and an unconventional monetary policy shock. The last column reports the $R^2$ of the common components (factors and observables).*
**Equal to unity by construction.*

Note how the contribution of the conventional monetary policy shock is higher for macroeconomic variables related to the real sector, such as output, income and the labor market, whereas the contribution of the unconventional monetary policy shock is the greater for the interest rates and spreads and for the money, credit and financial condition indices, hence to variables more related to the financial sector. This is consistent with the theoretical transmission mechanisms of QE, which are based mainly on changes to the entire term structure of interest rates. However, it seems that the QE shock affects the variability of variables related to consumption to a greater extent, and that a conventional shock affects exchange rates more, although it is largely influenced by monetary policy in both regimes. As for the last column, the $R^2$ of the common component is high for the group related to interest rates and spreads. This allows us to place particular confidence in the results related to these variables, which are crucial in understanding the differences between the transmission channels of the two monetary policy regimes.

# 5 Robustness checks

To check the robustness of the results outlined in section 4, we carry out a set of additional exercises. Firstly, increasing the number of factors to 3 or 4 does not seem to change the main macroeconomic implications of the impulse response functions, albeit at the cost of slightly decreased significance. As outlined in Bernanke et al. (2005), the parameter estimates become less precise as factors are added to the state (MS-VAR) equation. For this reason, we adhere to a sparing choice for our main analysis. Secondly, we check whether the selected Cholesky identification affects our results by switching the order of inflation and unemployment rates, so that the former is now allowed to respond simultaneously to the latter. The results of this exercise are strikingly similar to our preferred ordering, in accordance with Korobilis (2013), both in terms of the evolution of the time-varying transition probabilities and the IRFs. Lastly, we check the robustness of our results by substituting the shadow rate developed by Wu and Xia (2016) with the shadow short rate developed by Krippner (2013). Figure 11 shows the time-varying transition probabilities of the MS-FAVAR, which evolve in a very similar fashion to our preferred specification in Figure 2. Figure 12 illustrates the impulse response functions of the selected variables resulting from this exercise. Both the responses of the observables of the MS-VAR equation and the variables of the informational set that describe the main transmission channels of QE respond according to our previous results, confirming both the macroeconomic implications and the statistical significance of our original analysis.

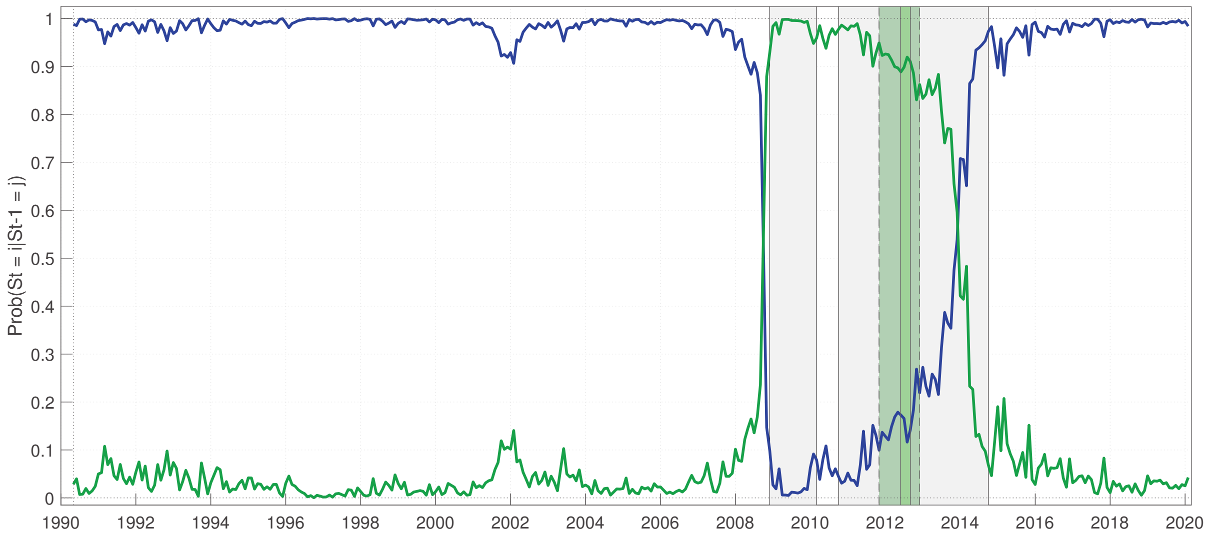


*Figure 11: Time-varying transition probabilities with the shadow rate of Krippner (2013). The dark blue line corresponds to $Prob(S_t = 0|S_{t-1} = 1)$; the dark green line corresponds to $Prob(S_t = 1|S_{t-1} = 0)$. They gray areas and the light green area correspond to the periods of implementation of Quantitative Easing and Operational Twist respectively. The dark green areas are periods where QE and OT overlap.*

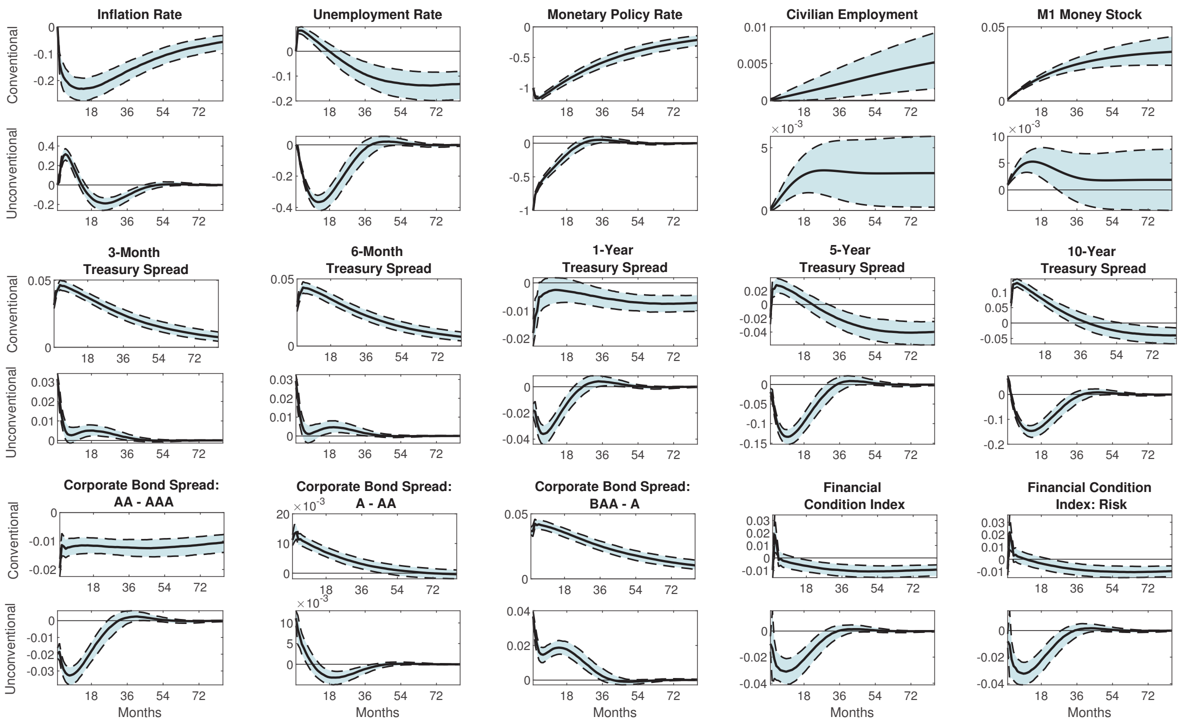


*Figure 12: Impulse responses of selected variables with the shadow rate of Krippner (2013). IRFs to an expansionary one standard deviation conventional and unconventional monetary policy shock using the shadow rate developed in Krippner (2013). The black solid lines are median responses, while the light blue areas correspond to 68% confidence bounds.*

## 6 Conclusions

In this paper, we analyzed the overall effect of the Federal Reserve large-scale asset purchase programs and shed light on their transmission mechanisms from the financial sector to the real economy. By including a shadow-augmented interest rate in a Markov switching factor-augmented vector autoregression with time-varying transition probabilities, we can extract the relevant information from a large set of variables and assess the transmission channels of both conventional and unconventional monetary policy measures within a unique macro-econometric framework. We estimate the model with a fully Bayesian approach, which allows us to treat factors as unknown parameters and augment the usual informational set of variables with suitable indicators for the main theoretical transmission channels of QE. The results of the estimation highlight a dominant role for the duration risk (portfolio-rebalancing) and the credit channels, a marginal role for the default risk channel and rule out any significant role for the signaling channel of QE. We find that decreasing spreads for long-term Treasury Bills and relatively better overall financial conditions are two distinctive features of the unconventional monetary policy regime. The former of the two is consistent with the presence of an excess demand for longer-maturity assets from some preferred-habitat investors, who do not perceive assets of different maturities as perfect substitutes. This, in turn, increases the price of longer-term assets, leading to an increase in their owners' wealth and, ultimately, to economic growth via increased loan volumes.

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## Appendix A: Data series

Tables 2 and 3 list the time series used in the informational set $\boldsymbol{X_t}$ and in the vector of observables $\boldsymbol{Y_t}$ respectively. The series are on monthly frequency, spanning the period 1990:M1 - 2020:M2. They are taken from the FRED-MD data set of McCracken and Ng (2016), with the exception of the long US corporate bond yields, which are taken from the Thomson Reuters Datastream, from which we also compute the corresponding spreads. The tables contain: the series number, series mnemonic, transformation code and series description. The transformation codes are 1 - no transformation; 2 - first difference; 4 - logarithm; 5 - first difference of logarithm; 6 - second difference of logarithm.

*Table 2: Series used for the informational set $\boldsymbol{X_t}$*

| | | *Output and Income* | |
|---|---|---|---|
| *#* | *Mnemonic* | *Tcode* | *Description* |
| 1 | RPI | 5 | Real Personal Income |
| 2 | W875RC1 | 5 | Real Personal Income Ex Transfer Receipts |
| 3 | INDPRO | 5 | IP Index |
| 4 | IPFPNSS | 5 | IP: Final Products and Nonindustrial Supplies |
| 5 | IPFINAL | 5 | IP: Final Products (Market Group) |
| 6 | IPCONGD | 5 | IP: Consumer Goods |
| 7 | IPDCONGD | 5 | IP: Durable Consumer Goods |
| 8 | IPNCONGD | 5 | IP: Nondurable Consumer Goods |
| 9 | IPBUSEQ | 5 | IP: Business Equipment |
| 10 | IPMAT | 5 | IP: Materials |
| 11 | IPDMAT | 5 | IP: Durable Materials |
| 12 | IPNMAT | 5 | IP: Nondurable Materials |
| 13 | IPMANSICS | 5 | IP: Manufacturing (SIC) |
| 14 | IPB51222S | 5 | IP: Residential Utilities |
| 15 | IPFUELS | 5 | IP: Fuels |
| 16 | CUMFNS | 5 | Capacity Utilization: Manufacturing |
| | | *Labor Market* | |
| 17 | HWI | 2 | Help-Wanted Index for United States |
| 18 | HWIURATIO | 2 | Ratio of Help Wanted/No. Unemployed |
| 19 | CLF16OV | 5 | Civilian Labor Force |
| 20 | CE16OV | 5 | Civilian Employment |
| 21 | UEMPMEAN | 2 | Average Duration of Unemployment (Weeks) |
| 22 | UEMPLT5 | 5 | Civilians Unemployed – Less Than 5 Weeks |
| 23 | UEMP5TO14 | 5 | Civilians Unemployed for 5-14 Weeks |
| 24 | UEMP15OV | 5 | Civilians Unemployed – 15 Weeks & Over |
| 25 | UEMP15T26 | 5 | Civilians Unemployed for 15-26 Weeks |
| 26 | UEMP27OV | 5 | Civilians Unemployed for 27 Weeks and Over |
| 27 | CLAIMSx | 5 | Initial Claims |

| | | | |
|---|---|---|---|
| 28 | PAYEMS | 5 | All Employees: Total Nonfarm |
| 29 | USGOOD | 5 | All Employees: Goods-Producing Industries |
| 30 | CES1021000001 | 5 | All Employees: Mining and Logging: Mining |
| 31 | USCONS | 5 | All Employees: Construction |
| 32 | MANEMP | 5 | All Employees: Manufacturing |
| 33 | DMANEMP | 5 | All Employees: Durable Goods |
| 34 | NDMANEMP | 5 | All Employees: Nondurable Goods |
| 35 | SRVPRD | 5 | All Employees: Service-Providing Industries |
| 36 | USTPU | 5 | All Employees: Trade, Transportation & Utilities |
| 37 | USWTRADE | 5 | All Employees: Wholesale Trade |
| 38 | USTRADE | 5 | All Employees: Retail Trade |
| 39 | USFIRE | 5 | All Employees: Financial Activities |
| 40 | USGOVT | 5 | All Employees: Government |
| 41 | CES0600000007 | 1 | Avg Weekly Hours: Goods-Producing |
| 42 | AWOTMAN | 2 | Avg Weekly Overtime Hours: Manufacturing |
| 43 | AWHMAN | 1 | Avg Weekly Hours: Manufacturing |
| 44 | CES0600000008 | 6 | Avg Hourly Earnings: Goods-Producing |
| 45 | CES2000000008 | 6 | Avg Hourly Earnings: Construction |
| 46 | CES3000000008 | 6 | Avg Hourly Earnings: Manufacturing |
| | | | *Housing* |
| 47 | HOUST | 4 | Housing Starts: Total New Privately Owned |
| 48 | HOUSTNE | 4 | Housing Starts, Northeast |
| 49 | HOUSTMW | 4 | Housing Starts, Midwest |
| 50 | HOUSTS | 4 | Housing Starts, South |
| 51 | HOUSTW | 4 | Housing Starts, West |
| 52 | PERMIT | 4 | New Private Housing Permits (SAAR) |
| 53 | PERMITNE | 4 | New Private Housing Permits, Northeast (SAAR) |
| 54 | PERMITMW | 4 | New Private Housing Permits, Midwest (SAAR) |
| 55 | PERMITS | 4 | New Private Housing Permits, South (SAAR) |
| 56 | PERMITW | 4 | New Private Housing Permits, West (SAAR) |
| | | | *Consumption, Orders and Inventories* |
| 57 | DPCERA3M086SBEA | 5 | Real Personal Consumption Expenditures |
| 58 | CMRMTSPLx | 5 | Real Manu. and Trade Industries Sales |
| 59 | RETAILx | 5 | Retail and Food Services Sales |
| 60 | AMDMNOx | 5 | New Orders for Durable Goods |
| 61 | AMDMUOx | 5 | Unfilled Orders for Durable Goods |
| 62 | BUSINVx | 5 | Total Business Inventories |
| 63 | ISRATIOx | 2 | Total Business: Inventories to Sales Ratio |
| | | | *Money, Credit and Financial Condition Indices* |
| 64 | M1SL | 5 | M1 Money Stock |
| 65 | M2SL | 5 | M2 Money Stock |
| 66 | M2REAL | 5 | Real M2 Money Stock |
| 67 | TOTRESNS | 5 | Total Reserves of Depository Institutions |
| 68 | BUSLOANS | 5 | Commercial and Industrial Loans |
| 69 | REALLN | 5 | Real Estate Loans at All Commercial Banks |

| | | | |
|---|---|---|---|
| 70 | NFCI | 1 | National Financial Condition Index (US) |
| 71 | NFCIRISK | 1 | National Financial Condition Index (US): Risk subindex |
| | | *Interest and Exchange Rates* | |
| 72 | CP3Mx | 1 | 3-Month AA Financial Commercial Paper Rate |
| 73 | TB3MS | 1 | 3-Month Treasury Bill: |
| 74 | TB6MS | 1 | 6-Month Treasury Bill: |
| 75 | GS1 | 1 | 1-Year Treasury Rate |
| 76 | GS5 | 1 | 5-Year Treasury Rate |
| 77 | GS10 | 1 | 10-Year Treasury Rate |
| 78 | GS20 | 1 | 20-Year Treasury Rate |
| 79 | Long-AAA | 1 | Long AAA U.S. Corporate |
| 80 | Long-AA | 1 | Long AA U.S. Corporate |
| 81 | Long-A | 1 | Long A U.S. Corporate |
| 82 | Long-BAA | 1 | Long BAA U.S. Corporate |
| 83 | TB3SMFFM | 1 | 3-Month Treasury C Minus FEDFUNDS |
| 84 | TB6SMFFM | 1 | 6-Month Treasury C Minus FEDFUNDS |
| 85 | T1YFFM | 1 | 1-Year Treasury C Minus FEDFUNDS |
| 86 | T5YFFM | 1 | 5-Year Treasury C Minus FEDFUNDS |
| 87 | T10YFFM | 1 | 10-Year Treasury C Minus FEDFUNDS |
| 88 | T20YFFR | 1 | 20-Year Treasury C Minus FEDFUNDS |
| 89 | sAA-AAA | 1 | Long AA Minus Long AAA U.S. Corporate Bond Rate |
| 90 | sA-AA | 1 | Long A Minus Long AA U.S. Corporate Bond Rate |
| 91 | sBAA-A | 1 | Long BAA Minus Long A U.S. Corporate Bond Rate |
| 92 | EXSZUSx | 5 | Switzerland / U.S. Foreign Exchange Rate |
| 93 | EXJPUSx | 5 | Japan / U.S. Foreign Exchange Rate |
| | | *Prices* | |
| 94 | WPSFD49207 | 6 | PPI: Finished Goods |
| 95 | CUSR0000SAC | 6 | CPI : Commodities |
| 96 | CUSR0000SAD | 6 | CPI : Durables |
| 97 | CUSR0000SAS | 6 | CPI : Services |
| | | *Stock Market* | |
| 98 | S&P 500 | 5 | S&P's Common Stock Price Index: Composite |
| 99 | S&P: indust | 5 | S&P's Common Stock Price Index: Industrials |
| 100 | S&P div yield | 5 | S&P's Composite Common Stock: Dividend Yield |
| 101 | S&P PE ratio | 5 | S&P's Composite Common Stock: Price-Earnings Ratio |

*Table 3: Series used in the vector of observables* $\boldsymbol{Y_t}$

| *#* | *Mnemonic* | *Tcode* | *Description* |
|---|---|---|---|
| 102 | INFRATE | 1 | CPI Annual Inflation Rate: All Items in U.S. City Average |
| 103 | UNRATE | 1 | Civilian Unemployment Rate |
| 104 | SHADOWFFR | 1 | Shadow-augmented Effective Federal Funds Rate |

## Appendix B: Prior Distributions Setup

This Appendix describes the priors used in the empirical application. Following Huber and Fischer (2018) we set proper priors.

### Observation equation

Recall equation (2):

$$\boldsymbol{X}_t = \boldsymbol{\Lambda}^y \boldsymbol{Y}_t + \boldsymbol{\Lambda}^f \boldsymbol{F}_t + \boldsymbol{e}_t, \quad \boldsymbol{e}_t \sim \mathcal{N}(0, \Sigma_{\boldsymbol{e}}),$$

and collect the loadings of both observables and factors in the $M \times (K+N)$ matrix $\boldsymbol{\Lambda} = (\boldsymbol{\Lambda}^y, \boldsymbol{\Lambda}^f)$ and let its elements be denoted by $\boldsymbol{\lambda} = vec(\boldsymbol{\Lambda})$. We impose on $\lambda_j$, for $j = 1, \ldots, M(K+N)$, a mixture of Normal distributions such that:

$$\lambda_j \mid \iota_j \sim \mathcal{N}\left(0, \varrho_0^2\right) \iota_j + \mathcal{N}\left(0, \varrho_1^2\right)(1-\iota_j), \tag{12}$$

where $\varrho_0$ and $\varrho_1$ are hyperparameters controlling the tightness of the Gaussian priors, and $\iota_j$ for $j = 1, \ldots, M(K+N)$ are binary random variables such that:

$$\iota_j \sim Bernoulli(\underline{\rho}_j), \tag{13}$$

where $\underline{\rho}_j = Prob(\iota_j = 1)$ is the inclusion probability of a variable in equation (2).
Finally, for the variance-covariance matrix $\boldsymbol{\Sigma}_e$, we use Inverse-Gamma priors ($\mathcal{IG}$) for the main diagonal elements:

$$\varsigma_j \sim \mathcal{IG}(\underline{\alpha}_j, \underline{\beta}_j), \tag{14}$$

where $\underline{\alpha}_j$ and $\underline{\beta}_j$ are the shape and scale hyperparameters.

### Probit equation

Recall equation (7), which we use to model the time-variation of the transition probabilities:

$$r_t = \gamma_{0,i} + \boldsymbol{\gamma}' \boldsymbol{\zeta}_{t-1} + \epsilon_t.$$

Similar to the choice for the observation equation, we impose a mixture of Gaussians on the $g$th element of equation (7), for $g = 1, \ldots, G$, such that:

$$\gamma_g \mid \delta_g \sim \mathcal{N}\left(0, \tau_0^2\right) \delta_g + \mathcal{N}\left(0, \tau_1^2\right)(1-\delta_g), \tag{15}$$

where the prior variances are such that $\tau_0^2 > \tau_1^2$, and $\delta_g$ for $g = 1, \ldots, G$ are binary random variables such that:

$$\delta_g \sim Bernoulli(\underline{p}_g), \tag{16}$$

where $\underline{p}_g = Prob(\delta_g = 1)$ is the inclusion probability in equation (7).
The regime-specific intercept term is also normally distributed:

$$\gamma_{0,i} \sim \mathcal{N}(0, \varphi_i), \tag{17}$$

with symmetric prior variances $\varphi_0 = \varphi_1$ for the two monetary policy regimes.

### Markov-switching VAR equation

Recall equation (3):

$$\boldsymbol{z}_t = \boldsymbol{a}_{S_t} + \boldsymbol{A}_{1,S_t}\boldsymbol{z}_{t-1} + \cdots + \boldsymbol{A}_{Q,S_t}\boldsymbol{z}_{t-Q} + \boldsymbol{\varepsilon}_t,$$

and collect the VAR coefficients in $\boldsymbol{A}_{S_t} = \boldsymbol{a}_{S_t} + \boldsymbol{A}_{1,S_t} + \cdots + \boldsymbol{A}_{Q,S_t}$. We impose a set of conditionally conjugate priors on the state equation as in Huber and Fischer (2018):

$$\text{vec}\left(\boldsymbol{A}_{S_t}\right) \mid \boldsymbol{\Sigma}_{S_t} \sim \mathcal{N}\left(\text{vec}(\underline{\boldsymbol{A}}), \boldsymbol{\Sigma}_{\varepsilon,S_t} \otimes \underline{\boldsymbol{V}}_A(\theta_{S_t})\right) \tag{18}$$

where $\underline{\boldsymbol{A}}$ is $C \times R$, $\underline{\boldsymbol{V}}_A(\theta_{S_t})$ is $C \times C$, respectively prior mean and regime-specific prior variance-covariance matrices. $\underline{\boldsymbol{A}}$ and $\underline{\boldsymbol{V}}_A(\theta_{S_t})$ are specified such that:

$$E\left[\boldsymbol{A}_{q,S_t}\right]_{ij} = \begin{cases} \underline{a}_i & \text{for } q = 1 \text{ and } i = j \\ 0 & \text{for } q > 1 \text{ and } i \neq j, \end{cases}$$

$$\text{Var}\left[\boldsymbol{A}_{q,S_t}\right]_{ij} = \frac{\theta^2_{S_t}}{q^2}\frac{\sigma_i}{\sigma_j},$$

with $q = 1, \ldots, Q$ lag order, $\underline{a}_i$ prior mean related to lag one, $i, j = 1, \ldots, R$ variable units and $\sigma_i$ and $\sigma_j$ empirical OLS standard deviations of the univariate regressions on $\boldsymbol{z}_t = [\boldsymbol{F}'_t, \boldsymbol{Y}'_t]'$. Furthermore, the variance-covariance matrix $\boldsymbol{\Sigma}_{\varepsilon,S_t}$ has the following inverse-Wishart ($\mathcal{IW}$) prior specification:

$$\boldsymbol{\Sigma}_{\varepsilon,S_t} \sim \mathcal{IW}(\underline{\boldsymbol{\Psi}}, \underline{\nu}), \tag{19}$$

with $\underline{\boldsymbol{\Psi}}$ $R \times R$ prior scale matrix and $\underline{\nu}$ prior degrees of freedom of the distribution.
Finally, we impose Gamma ($\mathcal{G}$) priors on the regime-switching parameters $\theta_{S_t}$ such that:

$$\theta_{S_t} \sim \mathcal{G}(c_0, c_1), \tag{20}$$

with $c_0$ and $c_1$ hyperparameters.
Table 4 illustrates the values used for the set of prior hyperparameters.

*Table 4: Value choices for the hyperparameters*

| *Equation* | *Hyperparameter* | *Value* |
|---|---|---|
| Observation Equation | $\varrho_0^2$ | 10 |
| | $\varrho_1^2$ | 0.1 |
| | $\underline{\alpha}_j = \underline{\beta}_j$ | 0.01 |
| Probit Equation | $\tau_0^2$ | 1 |
| | $\tau_1^2$ | 0.1 |
| | $\varphi_0 = \varphi_1$ | $10^2$ |
| Markov-switching VAR Equation | *intercept* | $\mathcal{N}(0, 10^2)$ |
| | $c_0 = c_1$ | 0.01 |

## Appendix C: Diffuse Prior specifications

In this section we provide a robustness check exercise where a set of impulse response functions is estimated using more diffuse priors. Figure 13 shows the results associated with a less informative Gamma ($\mathcal{G}$) prior on the regime-switching parameters $\theta_{S_t}$ of the Markov switching VAR equation, and to a less informative Inverse-Gamma ($\mathcal{IG}$) on the main diagonal elements $\varsigma_j$ of the variance-covariance matrix $\mathbf{\Sigma}_e$ of the observation equation. The prior distributions are chosen such that $\theta_{S_t} \sim \mathcal{G}(c_0, c_1)$ with $c_0 = c_1 = 1$ and $\varsigma_j \sim \mathcal{IG}(\underline{\alpha}_j, \underline{\beta}_j)$ with $\underline{\alpha}_j = \underline{\beta}_j = 3$, effectively rendering both priors less influential in the estimation of the model. The results are both qualitatively and quantitatively similar to those of our main analysis, illustrating that choosing less informative priors for the parameters does not significantly affect the estimation of the posterior distributions of the model.

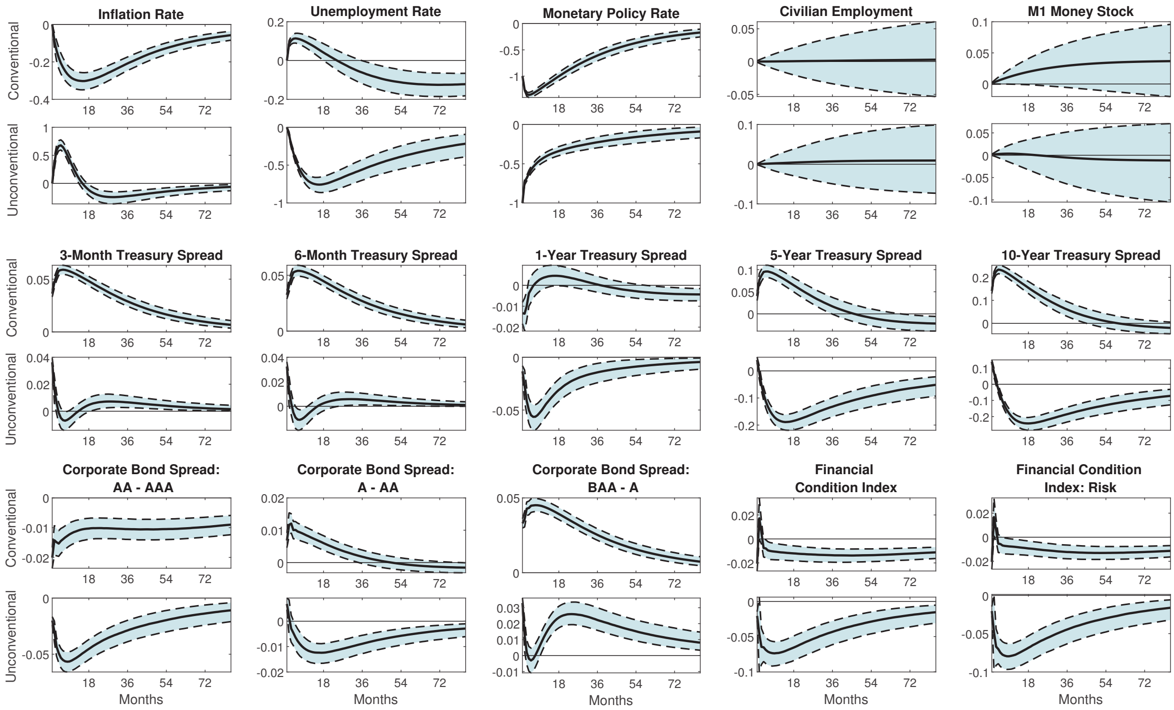


*Figure 13: Impulse responses to an expansionary one standard deviation conventional and unconventional monetary policy shock with $\theta_{S_t} \sim \mathcal{G}(1,1)$ and $\varsigma_j \sim \mathcal{IG}(3,3)$. The black solid lines are median responses, while the light blue areas correspond to 68% confidence bounds.*

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