# Financial Conditions and Monetary Policy: The Importance of Non-Linear Effects

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## Abstract

We estimate a Markov-switching Vector Autoregression (**MS-VAR**) and a Markov-switching Dynamic Stochastic General Equilibrium (**MS-DSGE**) macroeconomic model with financial frictions in long-term debt instruments developed by Carlstrom, Fuerst and Paustian (2017, AEJ: Macro) to provide evidence of the importance of allowing for switching parameters (non-linearities) and switching variance (heteroscedasticity) when analyzing macro-financial linkages in the US. Based on a Maximum Likelihood model fit criterion, the introduction of Markov switching in parameters and variances improves the fit of a macroeconomic VAR model with financial variables, with the best fit in an unrestricted model with two switches in coefficients and three switches in variances (*2c3v*). Likewise, the introduction of Markov switching in parameters and especially in variances, also greatly improves the Maximum Likelihood fit of the DSGE macroeconomic model with financial frictions, with the best fit in the model with two regimes for the parameters governing the financial market segmentation that is associated with financial frictions, two regimes for the monetary policy interest rate response to the term premium, and three regimes for the credit shock volatility (*2S2R3V*). To fit the data, an estimated time-invariant DSGE produces larger shocks relative to a DSGE model with Markov-switching in parameters. An estimated DSGE without Markov-switching in parameters misinterprets structural regime switches as large shocks events. Meanwhile, an estimated DSGE without Markov-switching in shocks overestimates the high coefficients regimes. The impulse response functions are markedly different depending on the regime the economy is under. Using the MS-DSGE model specification with the best fit to the data (*2S2R3V*) we: (i) provide evidence on how financial conditions have evolved in the US since 1962, (ii) show how the Federal Reserve Bank has responded to the evolution of term premiums, (iii) perform counterfactual analysis of the potential evolution of macroeconomic and financial variables under alternative financial conditions and monetary policy responses.

*Keywords: monetary policy, term-structure, financial frictions, Markov- switching VAR, Markov-switching DSGE, Bayesian maximum likelihood methods.*
*JEL classification: El2, E43, E44, E52, E58, C11.*

*"Over the past three years, people around the world have experienced an unprecedented series of shocks, albeit to varying degrees. [...] One visible impact of these shifts has been the return of high inflation globally, which has caused anguish for many people. Central banks have responded by tightening monetary policy and, while progress is being made, the fight against inflation is not yet won. But these shifts could also have profound longer-term implications. There are plausible scenarios where we could see a fundamental change in the nature of global economic interactions. In other words, we may be entering an age of shifts in economic relationships and breaks in established regularities. For policymakers with a stability mandate, this poses a significant challenge."*

*"Policymaking in an age of shifts and breaks," Christine Lagarde, president, European Central Bank, August 25, 2023.*

*"... a reason why statistically significant and macroeconomically important linkages have been elusive is because the importance of financial factors tends to be episodic in nature. In "normal times," firms make investment decisions on the basis of whether a project's expected rate of return exceeds the user cost of capital, and then having made that decision, seek the financing. In such times, the financing decision is, in some sense, subordinate to the real-side decisions of the firm; credit "doesn't matter. In other times, when the financial system is not operating normally, financial frictions become important as lending terms and standards tighten, making the interest rate a much less reliable metric of the cost of funds, broadly defined. During such times, which we will call stress events; credit can seem like it is the only thing that matters."*

*Kirstin Hubrich and Robert J. Tetlow (2015). Financial stress and economic dynamics: The transmission of crises. Journal of Monetary Economics, 70: 100 -115.*

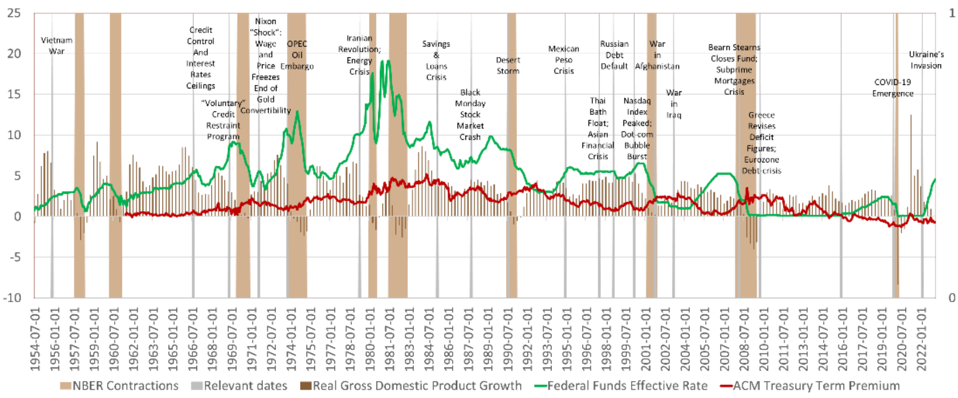
*"To the extent that the decline in forward rates can be traced to a decline in the term premium [...] the effect is financially stimulative and argues for greater monetary policy restraint, all else being equal. Specifically, if spending depends on long-term interest rates, special factors that lower the spread between short-term and long-term rates will stimulate aggregate demand. Thus, when the term premium declines, a higher short-term rate is required to obtain the long-term rate and the overall mix of financial conditions consistent with maximum sustainable employment and stable prices."*

*"Reflections on the Yield Curve and Monetary Policy," Ben S. Bernanke, chairman, Federal Reserve Bank, March 20, 2006.*

## 1. INTRODUCTION

Decreases (increases) in long-term interest rates, caused by compressions (dilations) of term premiums[1], could be financially expansive (contractive) and might require monetary policy restraints (stimulus).[2] Before discussing some of the potential mechanisms linking developments in long-term debt markets and the macroeconomy, it is useful to look at the evolution of the growth rate of real gross domestic product (GDP), the effective federal funds rate, and the term premium. Figure 1 shows these series together with the recessions identified by the NBER's Business Cycle Dating Committee. There is a strong negative correlation of −0.53 between the cyclical components of GDP and the term premium. Meanwhile the correlation among the cyclical components of the federal funds rate and the term premium is −0.36, and the correlation among the cyclical components of GDP and the federal funds rate is 0.47.[3]

*Figure 1. GDP growth, Federal Funds Rate and Term Premium: 1961Q1-2017Q4*




*Note: GDP is the growth rate of the real gross domestic product (GDPC1 in Fred Economic Data from the Federal Reserve Bank of St. Louis), federal funds rate is the effective federal funds rate (FEDFUNDS also in Fred Economic Data), term premium is the 10-year Treasury term premium computed following the methodology of Adrian, Crump and Moench (2013) and reported by the Federal Reserve Bank of New York (ACM10TP), and contractions are as dated by the NBER's Business Cycle Dating Committee.*

To investigate the relation between long-term debt markets and the macroeconomy, we estimate a Markov-switching vector autoregressive model (MS-VAR) following Hubrich and Tetlow (2015), where we replace the post-December 1988 Federal Reserve Board staff's

[1] Term premium is defined as the extra compensation required by investors for bearing interest rate risk associated with short-term yields not evolving as expected.

[2] See the above quote by Bernanke (2006) and Rudebusch et al. (2006) that show that a decline in the term premium has typically been associated with higher future GDP growth.

[3] Cyclical components are produced by applying a Hodrick Prescott filter. We thank Robert E. Lucas for his suggestion of having the high-frequency movements removed using a statistical filter to show if there is a long-run relationship between these three series in a similar way he did to analyze inflation and money growth at https://files.stlouisfed.org/files/htdocs/publications/review/2014/q3/lucas.pdf

financial conditions index with the post-January 1962 Federal Reserve of New York's term premium calculated by Adrian et al. (2013), to identify stress events. First, we analyze if the data favors a Markov-switching specification where coefficients and/or variances can switch relative to a time-invariant Gaussian vector autoregression (VAR) model. Our results show that the best fit is attained when we allow for two independent Markov states governing the coefficient switching and three independent Markov states governing the variance switching in all equations, providing evidence of nonlinear and non-Gaussian phenomena. Second, using that preferred specification, we identify the probability of being in a specific coefficient and a specific variance state. Third, the impulse response functions show big differences in the transmission of shocks across different coefficient and variance regimes.

To give an economic interpretation to the switching parameters and switching variance, we compare Bayesian estimations of a time-invariant Gaussian dynamic stochastic general equilibrium (DSGE) model versus different specifications of a Markov-switching dynamic stochastic general equilibrium (MS-DSGE) version of the macroeconomic model with financial frictions in long-term debt instruments developed by Carlstrom et al. (2017). First, we confirm that allowing for regime switches in parameters and specially in shock variance greatly improves the Marginal Likelihood fit of the model to the data. In addition, we show the difference in the parameters estimates and impulse response functions of the DSGE and MS-DSGE models. Also, we analyze the consequence of restricting Markov-switching for the identification of parameters and variance.

We use the MS-DSGE model with the best fit to the data to: 1) study how financial conditions, as measured by the degree of financial frictions and volatilities of credit market shocks, have evolved in the US since 1962; 2) measure how the Federal Reserve has responded to the evolution of term premiums; and 3) perform counterfactual analysis of the potential evolution of macroeconomic and financial variables under alternative financial conditions, monetary policy responses, and credit shock volatilities. In this estimation there are different, well defined, regimes of high and low financial frictions, high and low monetary policy response to the term premium and high (, medium) and low credit shock volatilities regimes.

The counterfactual exercises allow to separately analyze the effects of financial frictions, monetary policy responses, and the volatility of credit market shocks, in the evolution of macroeconomic and financial variables. We analyzed six episodes when the estimation assigns a high probability[4] to high financial frictions and/or medium or high shock volatilities. In three of them there was a high monetary policy response to financial factors: 1978Q4-1983Q4 which helped to mitigate inflation at the cost of economic activity, and the 1990Q2-1993Q4 and 2010Q1-2011Q4 episodes in which the high response served to mitigate economic contractions. Meanwhile, in the three episodes where low response to financial factors is observed, if the monetary authority had responded more aggressively, from 1971Q1-1978Q3 it could have attained lower inflation at the cost of lower GDP, from 2000Q4-2004Q4 it could have delayed the GDP contraction to 2002Q3, but this would have been deeper and inflation larger, and in 2006Q1-2009Q4 it might have precipitated the GDP contraction. The presence of high financial frictions and high shock volatility makes

[4] We refer to *large* probability if the estimated probability of a given Markov-state is larger or equal than 50 percent.

recessions deeper and recoveries more sluggish, showing the importance of the financial-macroeconomic nexus.

The paper is organized as follows. Section 2 presents the MS-VAR model including its specification and results and compare them with the time-invariant Gaussian VAR model. Section 3 presents a MS-DSGE version of a model of segmented financial markets where financial institutions' net worth limits the degree of arbitrage across the term structure (a financial friction), a *loan-in-advance* constraint that increases the private cost of purchasing investment goods (creating real effects of the financial frictions), and an augmented monetary policy with response to the term premium. Section 4 discusses the solution and estimation techniques of the MS-DSGE model. Section 5 compares the time-invariant Gaussian DSGE model with the MS-DSGE model showing evidence that switching coefficients and switching variance improves the model fit to the data; illustrates the effects of restricting MS in parameters and/or volatilities; and compares the identification of regimes and impulse response functions across model specifications. Section 6 presents the results of the MS-DSGE model with the best Maximum Likelihood fit, showing first the parameter estimates; then the impulse response functions for the different regimes associated to financial frictions, monetary policy and credit shock volatilities; after this we present the regimes probabilities; and finally, counterfactual exercises to analyze the role of financial frictions, monetary policy and credit shock volatilities in the evolution of financial and macroeconomic variables in the 1962- 2017 period. Section 7 presents our conclusions.

## 2. MS-VAR MODEL

In this section we present the MS-VAR model specification and the estimation results which 1) provide evidence on the benefit of allowing for Markov switching in coefficients and variances, while identifying the model with the best goodness-of-fit to the data, which is the one with two-coefficient switching and two-variance switching (*2c3v*), 2) to simplify the comparison with the time-invariant Gaussian VAR model (*1c1v*), we give the coefficient and variances regime probabilities for a model with two-coefficient switching and two-variance switching (*2c2v*), and 3) compare the impulse response functions of the (*1c1v*) versus (*2c2v*). The regime probabilities and impulse response functions for the model with the largest posterior mode (*2c3v*) are provided in Annex 2 and Annex 3, respectively.

### 2.1 Model specification

We introduce a MS-VAR to explore if macroeconomic and financial data provide evidence of switching parameters and switching variance, and to identify periods of high financial stress in the studied sample for the US economy, and hence highlight the importance of introducing these features in a structural modelling framework. We follow the approach presented by Hubrich and Tetlow (2015), which estimates a MS-VAR using the Financial Stress Index (FSI) to measure financial stress, but instead, we propose to use the term premium calculated by Adrian et al. (2013), that we will also use in our structural MS-DSGE, measure "*financial frictions*".

This specification adopts the spirit of smoothly time-varying parameters in VAR models presented by Primiceri (2005), Cogley and Sargent (2005), and Bianchi and Melosi

(2017). Following the notation of Hubrich and Tetlow (2015), the nonlinear system can be written as follows:

$$\boldsymbol{y}_t'\boldsymbol{A_0}(\boldsymbol{s}_t^c) = \sum_{l=1}^{p} \boldsymbol{y}_{t-1}'\boldsymbol{A}_l(\boldsymbol{s}_t^c) + \boldsymbol{z}_t'\boldsymbol{B}(\boldsymbol{s}_t^c) + \boldsymbol{\varepsilon}_t'\boldsymbol{\Xi}^{-1}(\boldsymbol{s}_t^v) \qquad (1)$$

where $\boldsymbol{y_t}$ is a $nx1$ vector of endogenous variables and $\boldsymbol{A_0}(\boldsymbol{s}_t^c)$ and $\boldsymbol{A_l}(\boldsymbol{s}_t^c)$ are $nxn$ matrices of Markov-switching parameters associated to the contemporaneous and lagged endogenous state variables, respectively; $\boldsymbol{z_t}$ is a $nx1$ matrix of exogenous variables and $\boldsymbol{B}(\boldsymbol{s}_t^c)$ is a $nxn$ matrix of Markov-switching parameters of the exogenous variables; $\boldsymbol{\varepsilon_t}$ is a vector of innovations and $\boldsymbol{\Xi}^{-1}(\boldsymbol{s}_t^v)$ is a matrix of Markov-switching variances. $\boldsymbol{s^m}$, $\boldsymbol{m} = \{\boldsymbol{c}, \boldsymbol{v}\}$ are unobservable (latent) state variables, one for intercepts and coefficients, $\boldsymbol{c}$, and one for variances, $\boldsymbol{v}$. The values of $\boldsymbol{s}_t^m$ are elements of $\{\boldsymbol{1}, \boldsymbol{2}, \cdots, \boldsymbol{h^m}\}$ and evolve according to a first-order Markov process:

$$\boldsymbol{Pr}(\boldsymbol{s}_t^m = \boldsymbol{i} | \boldsymbol{s}_{t-1}^m = \boldsymbol{k}) = \boldsymbol{p}_{ik}^m, \qquad \boldsymbol{i}, \boldsymbol{k} = \boldsymbol{1}, \boldsymbol{2}, \cdots, \boldsymbol{h^m}$$

We use quarterly data-series for a sample from 1962Q1 to 2017Q3. In the MS-VAR estimation, our set of endogenous variables is: $\boldsymbol{y_t} = [\boldsymbol{C}, \boldsymbol{P}, \boldsymbol{R}, \boldsymbol{M}, \boldsymbol{Tp}]'$, where $\boldsymbol{C}$ denotes the quarterly growth in personal consumption expenditures; $\boldsymbol{P}$ is CPI inflation excluding food and energy prices ; $\boldsymbol{R}$ is the nominal federal funds rate; $\boldsymbol{M}$ is growth in the nominal M2 monetary aggregate; and $\boldsymbol{Tp}$ represents the 10-year Treasury term premium reported by the Federal Reserve Bank of New York (ACM10TP). All the other data are taken from the Federal Reserve Bank of St. Louis. Following Sims et al. (2008), standard Minnesota priors are introduced to perform the Bayesian estimation.

## 2.2 Estimation results

### 2.2.1 Is there Markov-switching in coefficients and/or variances?

To determine if the data favors a Markov-switching specification where coefficients and/or variances can switch relative to a time-invariant Gaussian VAR model, we compare the goodness-of-fit of alternative models. Specifically, use #*c* to designate the possible states of the *Markov* chains that govern the slope and intercepts of the coefficients, and #*v* to indicate the possible states of the Markov chain governing the switching variance of the system, where # = 1, 2, and 3. In addition, we could restrict shifts in structural parameters to be constrained to a particular equation(s), indicating by post- fixing the letter(s) of the variable(s), *l* = {}, *C*, *P*, *R*, *M*, *T P*, where {} represents a null entry where parameters are allowed to change in all equations. Then, a model labeled as 1*c*1*v* corresponds to the time-invariant Gaussian VAR model, while 2*c*1*v* has two regimes for the coefficients with variations in all the equations and one regime for the variances, and 2*cTPR*3*v* has two regimes for the coefficients restricted to the term premium and interest rate equations and three regimes for the variances.

Table 1 displays the posterior mode for each specification of the model. The models are ordered in from worst to best goodness-of-fit criteria at the mode. Two results are worth noting: First, all the specifications allowing for regime switch are preferred to the constant model version, $1c1v$; second, the model with the best performance is $2c3v$, which allows for two-states in the Markov chain that controls the parameters in coefficients and intercepts simultaneously in all the equations of the system and three-states in the Markov chains that control variances; this result is similar to the selected specification in the estimation reported by Hubrich and Tetlow (2015) using the financial stress index for monthly data running from 1988M12 to 2011M12.

*Table 1: MS-VAR Estimation Results*

| Model specification | Posterior density |
|---|---|
| $1c1v$ | -2134.26 |
| $2c1v$ | -2116.98 |
| $1c2v$ | -2091.26 |
| $2c2v$ | -2087.19 |
| $2cTPR3v$ | -2074.19 |
| $2cTPC3v$ | -2071.41 |
| $2cTPCP3v$ | -2066.24 |
| $3c3v$ | -2052.12 |
| $2cTP3v$ | -2039.96 |
| $1c3v$ | -2014.16 |
| $2cRMC3v$ | -2008.31 |
| $2cTPRM3v$ | -1996.48 |
| $2cRM3v$ | -1986.39 |
| $2c3v$ | -1961.13* |

*Note: Posterior modes are in logarithms for the estimated models*

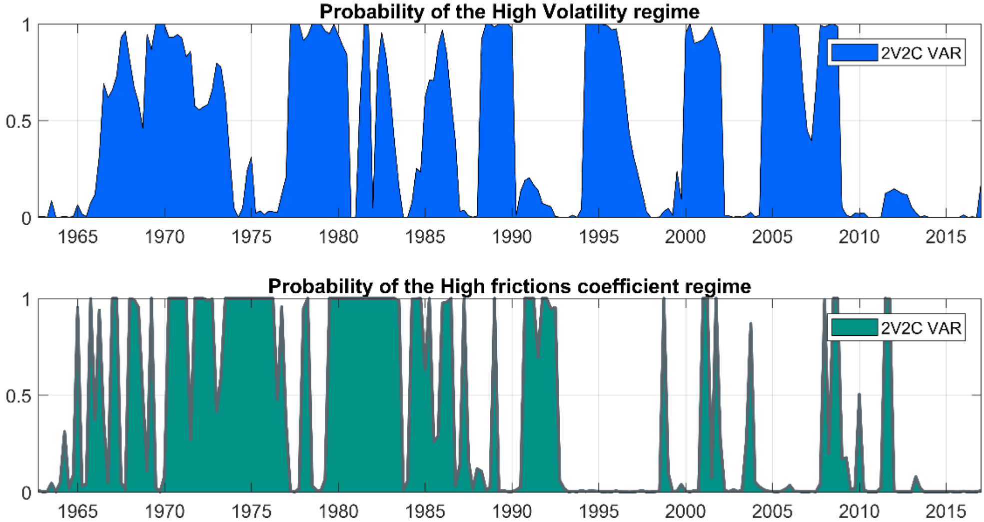
### 2.2.2 Probabilities of switching coefficients and variance states

Figure 2 displays the smoothed probabilities at the posterior mode for the high stress coefficient and the high stress variance for the $2c2v$ MS-VAR model, which will be useful to simplify the exposition of the comparison of a Markov-switching specification where coefficients and variances can switch relative to a time-invariant Gaussian VAR model. In Annex 2 we report the probabilities of switching coefficients of the high stress coefficient and the high and medium stress variance for the $2c3v$ MS-VAR model, which is the one with the best fit to the data.

### 2.2.3 VAR and MS-VAR Impulse Response Functions

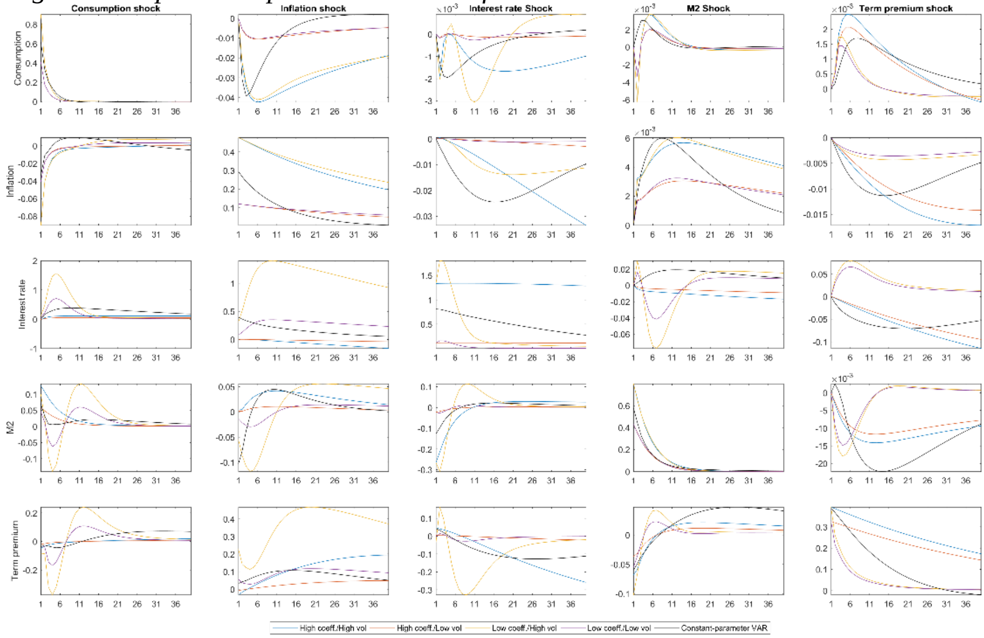
To show the difference between the impulse response functions of a Markov-switching specification where coefficients and variances can switch relative to a time- invariant Gaussian VAR model, Figure 3 displays the impulse response functions of the $1c1v$ VAR versus the $2c2v$ MS-VAR. In Annex 3 we report the impulse response functions for the $2c3v$ MS-VAR model, which is the one with the best fit to the data. Our estimations are consistent with empirical econometric approaches that model the role of financial frictions as a source of shock amplification allowing for Markov-switching dynamics using VAR models for the US economy (see Davig and Hakkio, 2010; and Hubrich and Tetlow, 2015). Guided by the evidence in this MS-VAR of varying coefficients and variances, we now move to a MS-DSGE model with macrofinancial linkages to analyze potential mechanisms.

*Figure 2: Smoothed Probabilities of MS-VAR Coefficients and Variances Regimes*




*Note: The top panel reports the probability of a high volatility regime. The second panel reports the probability of high frictions coefficient regime.*

*Figure 3: Impulse Response Functions of the 1c1v VAR and 2c2v MS-VAR*




*Note: High coefficient regimes are presented in blue/orange, while low coefficient regimes are shown in yellow/purple colors.*

# 3. MS-DSGE MODEL

Although the less restrictive MS-VAR econometric approach allows us to identify regime switches, it does not allow us to give an economic interpretation to the changes in parameters and variances. We will explore the possibility that the observed regime changes are related to shifts in financial conditions through changes in financial frictions and the volatility of credit market shocks. To do so, we use the model proposed by Carlstrom et al. (2017) and allow for regime-switching in the coefficient associated to financial frictions and in the variance regimes ordered by the volatility of credit market shocks. In addition, to analyze if monetary policy responded to those financial conditions, we allow for independent regime shifts of a term premium-augmented monetary policy interest rate reaction function. Using the model, we compare a time-invariant Gaussian DSGE with the Markov-Switching DSGE. Once we identify the model with the best fit, we identify how financial frictions, credit market shock volatilities, and monetary policy have evolved in the US since 1962. The estimated model provides us with a consistent framework to perform counterfactual analysis of what could have happened under alternative financial conditions, credit shock variances and monetary policy responses.

## 3.1 Model

This section presents the key elements of the DSGE model in Carlstrom et al. (2017) with our Markov-switching modification in the parameters that capture financial frictions, monetary policy responses and stochastic volatility of all the shocks in the model. Potential regime changes in financial frictions are captured by changes in the parameter associated with financial intermediaries' (FIs) portfolio adjustment costs, $\psi_n$ which is also related to the FIs holdup problem. We use a state variable, $\xi_t^{ff}$, to distinguish the level of financial friction regime at time $t$. Meanwhile, for regime changes in the monetary policy's response to the term premium, we use a state variable, $\xi_t^{mp}$, to differentiate among elasticities of short-term interest rates to the term premium $\tau_{tp}$ regime at time $t$. Concurrently, to allow for regime changes in the stochastic volatilities we model a third independent Markov-switching process and use a state variable $\xi_t^{vol}$ to distinguish the volatility regime at time $t$.

The economy consists of households, FIs and government agencies. Many of the ingredients are standard with the chief novelty coming from their assumptions on household-FI interactions. Specifically, households do not have access to long-term debt markets, while FI do, creating a credit market segmentation. Households face a loan-in-advance constraint to finance investment which gives market segmentation a relevant role for real allocations. FIs have a hold-up problem as they can default on depositors who could only recover a fraction $(1 - \Psi_t)$ of the FI's assets, where $\Psi_t$ is a decreasing function of FI's net worth, creating a financial-accelerator type of mechanism. FIs face portfolio adjustment costs which limits its ability to respond to changes in the government's relative supply of long-term debt having effects on lending and investment, as net worth and deposits cannot quickly sterilize central bank long-term debt purchases. Finally, the central bank interest rate reaction function is augmented with a potential response to the term-premium. These are key elements of the macro-financial-monetary policy nexus of the model highlighted here.

In Carlstrom et al. (2017), the reader can find the other elements of the model as the description of households' supply of monopolistically specialized labor as in Erceg et al. (2000), which serves to introduce wage rigidities and wage markup shocks. Also, there is the description of the perfectly competitive final good producer problem which yields the aggregation of a continuum of intermediate goods for aggregate supply. The monopolistic competitive intermediate goods producers' problem is introduced as in Yun (1996). These firms are also used to introduce neutral technology shocks and price rigidities and price markup shocks. The new capital producers' problem, which transforms investment goods into new capital goods through investment-adjustment costs, introduces an investment-specific technology shock.

### 3.1.1 Households

Each household chooses consumption, $C_t$, labor supply, $H_t$, short-term deposits in the financial intermediary, $D_t$, investment bonds, $F_t$, investment, $I_t$, and next-period physical capital, $K_{t+1}$, to maximize the optimization problem given by:

$$\max_{\{C_t, H_t, D_t, F_t, I_t, K_{t+1}\}_{t=0}^{\infty}} E_0 \left\{ \sum_{t=0}^{\infty} \beta^t e^{rn_t} ln(C_t - hC_{t-1}) - L\frac{H_t^{1+\eta}}{1+\eta} \right\} \tag{2}$$

subject to:

$$C_t + \frac{D_t}{P_t} + P_t^k I_t + \frac{F_{t-1}}{P_t} \leq W_t H_t + R_t^k K_t - T_t + \frac{D_{t-1}}{P_t} R_{t-1} + \frac{Q_t(F_t - \kappa F_{t-1})}{P_t}, \tag{3}$$

$$K_{t+1} \leq (1-\delta)K_t + I_t, \tag{4}$$

$$P_t^k I_t \leq \frac{Q_t(F_t - \kappa F_{t-1})}{P_t} \tag{5}$$

Before defining the variables and parameters, it is important to highlight that households do not have access to long-term bonds, while FIs do, creating a market segmentation. Also, very important for the macro-financial nexus, Equation 5 is a *loan-in-advance* constraint through which all investment purchases must be financed by issuing investment bonds, $F_t$, that are purchased by the FI. The endogenous behavior of the distortion related to the Lagrange multiplier of the *loan-in-advance* constraint is fundamental for the real effects arising from market segmentation.

In this optimization, $h \in (0,1)$ is the degree of habit formation, $\beta^t \in (0,1)$ is the discount factor which has intertemporal preferences shocks, $e^{rn}$, which follows the stochastic process $rn_t = \rho_{rn} rn_{t-1} + \sigma_{rn,\xi_t^{vol}} \varepsilon_{rn,t}$, where $\sigma_{rn,\xi_t^{vol}}$ is the standard deviation of the stochastic volatility of intertemporal preferences $\varepsilon_{rn,t} \sim i.i.d.\ N(0, \sigma_{rn}^2)$, whose $\xi_t^{vol}$ subscript denotes that it is allowed to change across regimes at time $t$. We follow the same convention in the notation for each shock. Aside from this switching volatility, the household problem does not have switching coefficients.

Equation 3 tells us that households' sources of income are: labor supply with real wage $W_t$; capital rents at a real rate $R_t^k$; previous period deposit holdings with gross nominal interest rate $R_{t-1}$; new issues of perpetuities of investment bonds $CI_t = F_t - \kappa F_{t-1}$ with price $Q_t$ and dividend flow from the FIs $div_t$.[5] Households use their resources to pay lump-sum taxes $T_t$; consume, deposit at FIs, buy investment goods with a real price of capital $P_t^k$ and pay for outstanding investment bonds. $P_t$ is the price level. Meanwhile, Equation 4 is the standard capital accumulation equation with depreciation rate $\delta$ and, as already mentioned, Equation 5 is the loan-in-advance constraint for investment purchases.

### 3.1.2 Financial Intermediaries

Financial intermediaries choose net worth, $N_t$, and dividends to maximize its value function, $V_t$, to solve the optimization problem given by:

$$V_t \equiv \max_{\{N_t, div_t\}_{t=0}^{\infty}} E_0\{\sum_{t=0}^{\infty}(\beta\zeta)^t \Lambda_t div_t\} \tag{6}$$

subject to the resource constraint:

$$div_t + N_t[1 + f(N_t)] \leq \frac{P_{t-1}}{P_t}[(R_t^L - R_{t-1}^d)L_t + R_{t-1}^d]N_t \tag{7}$$

and the incentive compatibility constraint that ensures that the FI repays deposits, given that depositors can seize at most a fraction $(1 - \Psi_t)$ of the FI's assets:

$$E_t V_{t+1} \geq \Psi_t E_t\left\{R_{t+1}^L\left(\frac{D_t}{P_t} + N_t\right)\right\} \tag{8}$$

where $\zeta \in (0,1)$ is an additional impatience to prevent that the short-term and long-term market segmentation vanishes through "excessive accumulation of net worth. $\Lambda_t$ is the household's marginal utility of consumption.

Regarding the resource constraint, FIs uses accumulated net worth, $N_t$, and short-term liabilities, $D_t$, to finance investment bonds, $F_t$, and the long-term bonds $B_t$. The FI's balance sheet is thus given by $\frac{B_t}{P_t}Q_t + \frac{F_t}{P_t}Q_t = \frac{D_t}{P_t} + N_t = L_t N_t$ where $Q_t$ is the price of a new- debt issue at time-$t$ and $L_t = \frac{\frac{D_t}{P_t}+N_t}{N_t}$, denotes leverage. Profits are given by $prof_t \equiv \frac{P_{t-1}}{P_t}[(R_t^L - R_{t-1}^d)L_{t-1} + R_{t-1}^d]N_{t-1}$, where $R_t^L \equiv \left(\frac{1+\kappa Q_t}{Q_{t-1}}\right)$ is the return on lending, $R_t^d$ is the return on deposits. On the left-hand side of equation (7), those profits are used to distribute dividends and accumulate net worth which has an adjustment cost

[5] The household also receives a profit flow from the intermediate good producers and the new capital producers, but to simplify notation, this part is omitted.

function $f(N_t) \equiv \frac{\psi_{n,\varepsilon_t^{ff}}}{2}\left(\frac{N_t - N_{ss}}{N_{ss}}\right)^2$ that dampens the ability of the FI to adjust the size of its portfolio in response to shocks. The $\varepsilon_t^{ff}$ subscript indicates that this financial market segmentation parameter, which is related to financial frictions, is allowed to change across regimes at time $t$.

Assuming that $\Psi_t \equiv \Phi_t\left[1 + \frac{1}{N_t}\left(\frac{E_t g_{t+1}}{E_t X_{t+1}}\right)\right]$, is a function of net worth in a symmetric manner with $f(N_t)$, the binding incentive constraint (8), which yields leverage as a function of aggregate variables but independent of each FI's net worth, is given by:

$$E_t \frac{P_t}{P_{t+1}} \Lambda_{t+1}\left[\left(\frac{R_{t+1}^L}{R_t^d} - 1\right) L_t + 1\right] = \Phi_t L_t E_t \frac{P_t}{P_{t+1}} \Lambda_{t+1} \frac{R_{t+1}^L}{R_t^d} \tag{9}$$

Then, the FI's optimal accumulation decision is given by

$$\Lambda_t[1 + N_t f'(N_t) + f(N_t)] = E_t \beta \zeta \Lambda_{t+1} \frac{P_t}{P_{t+1}}[(R_{t+1}^L - R_t^d)L_t + R_t^d] \tag{10}$$

where $\Phi_t \equiv e^{\phi_t}$ is a credit shock that in logarithms follows an AR(1) process

$$\phi_t = (1 - \rho_\phi)\phi_{ss} + \rho_\phi \phi_{t-1} + \sigma_{\phi,\xi_t^{vol}} \varepsilon_{\phi,t} \tag{11}$$

where $\sigma_{\phi,\xi_t^{vol}}$ is the standard deviation of the stochastic volatility of the credit shock, $\varepsilon_{\phi,t} \sim i.i.d.\ N(0, \sigma_\phi^2)$, whose $\xi_t^{vol}$ subscript denotes that it is allowed to change across regimes at time $t$. When we allow for regime switching in volatilities, regimes will be classified by the magnitude of this shock. Increases in $\phi_t$ will exacerbate the hold-up problem, and act as "credit shocks", which will increase the spread and lower real activity.

### 3.1.3 The Effect of Financial Friction

To gain further intuition of the financial frictions, first log-linearize the FI incentive compatibility constraint (equation 9) and the FI optimal net worth accumulation decision (equation 10) to get

$$E_t(r_{t+1}^L - r_t) = \upsilon l_t + \left[\frac{1 + L_{ss}(s-1)}{L_{ss} - 1}\right]\phi_t \tag{12}$$

and

$$\psi_{n,\xi_t^{ff}} n_t = \left[\frac{s L_{ss}}{1 + L_{ss}(s-1)}\right] E_t(r_{t+1}^L - r_t) + \left[\frac{(s-1)L_{ss}}{1 + L_{ss}(s-1)}\right] l_t \tag{13}$$

where $\upsilon \equiv \frac{1}{L_{ss} - 1}$ is the elasticity of the interest rate spread to leverage; $s$ denotes the gross steady-state premium. Equation 12 is quantitatively identical to the corresponding relation in the more complex costly state verification environment of Bernanke et al. (1999). Combining 12 and 13, we get the following expression:

$$E_t(r_{t+1}^L - r_t) = \frac{1}{L_{ss}} \boldsymbol{\psi}_{\boldsymbol{n},\boldsymbol{\xi}_t^{ff}} n_t + (s-1)\phi_t \tag{14}$$

This expression shows the importance of $\psi_{n,\xi_t^{ff}}$ for the supply of credit. If $\psi_{n,\xi_t^{ff}} = 0$, the supply of credit is perfectly elastic, independent of the financial intermediaries' net worth. As $\psi_{n,\xi_t^{ff}}$ becomes larger, the financial friction becomes more intense, and the supply of credit depends positively on the financial intermediaries' net worth.

#### 3.1.4 Fiscal Policy

Fiscal policy is entirely passive. Government expenditures are set to zero. Lump-sum taxes move endogenously to support the interest payments on the short- and long-term debt.

#### 3.1.5 Debt Market Policy

We consider a policy regime of exogenous debt. Long-term debt is assumed to follow:

$$b_t = \rho_1^b b_{t-1} + \rho_2^b b_{t-2} + \epsilon_{b,t} \tag{15}$$

where $b_t \equiv ln\left(\frac{\bar{B}_t}{B_{ss}}\right)$ and could fluctuate due to long bond purchases (QE) or changes in the mix of short debt to long debt in its maturity. An AR(2) process to be consistent with the QE policy and denote the persistence of the monetary policy shock.

#### 3.1.6 Central Bank Policy

We assume that the central bank follows a term premium $(tp_t)$ augmented Taylor rule over the short rate (T- bills and deposits):

$$ln(R_t) = \rho_{R,\xi_t^{mp}} ln(R_{t-1}) + \left(1 - \rho_{R,\xi_t^{mp}}\right)\left(\tau_{\pi,\xi_t^{mp}}\pi_t + \tau_{y,\xi_t^{mp}} y_t^{gap} + \tau_{tp,\xi_t^{mp}} tp_t\right) + \sigma_{r,\xi_t^{vol}}\varepsilon_{r,t} \tag{16}$$

where $y_t^{gap} \equiv \frac{Y_t - Y_t^f}{Y_t^f}$ denotes the deviation of output from its flexible price counterpart, $\pi_t$ t is CPI inflation rate, and $\varepsilon_{r,t}$ is an exogenous and auto-correlated policy shock with AR(1) coefficient $\rho_m$. The coefficient $\rho_{R,\xi_t^{mp}}$ captures the degree of persistence of the interest rate, and the parameters $\tau_{\pi,\xi_t^{mp}}$, $\tau_{y,\xi_t^{mp}}$ and $\tau_{tp,\xi_t^{mp}}$, capture the elasticity of the interest rate to inflation, output gap, and term premium, respectively. $\xi_t^{mp}$ indicates that these parameters can change across regime at time $t$. We will order regimes according to the relative response to the term premium. The term premium is defined as the difference between the observed yield on a ten-year bond and the corresponding yield implied by applying the expectation hypothesis of the term structure to the series of short rates.

# 4. SOLUTION AND ESTIMATION OF THE MS-DSGE MODEL

## 4.1 MS-DSGE Model Solution Methods

Given that the traditional stability concepts for constant DSGE models does not hold for the Markov-Switching case, to solve the linear version of the model we use the solution method proposed by Maih (2015),[6] which uses the minimum state variable (MSV)[7] concept to present the solution of the system. The Markov-Switching system can be cast in a state-space form by collecting all the endogenous variables in a vector $X$ and all the exogenous variables in a vector $Z$:

$$B_1\left(\xi_t^{sp}\right)X_t = E_t\left\{A_1\left(\xi_t^{sp},\xi_{t+1}^{sp}\right)X_{t+1}\right\} + B_2\left(\xi_t^{sp}\right)X_{t-1} + C_1\left(\xi_t^{sp}\right)Z_t$$
$$Z_t = R\left(\xi_t^{sp}\right)Z_{t-1} + \epsilon_t \qquad \text{with} \quad \epsilon_t \sim N(0,\, \Sigma^{vo}) \tag{17}$$

where $\xi^{sp}$ and $\xi^{vo}$ are Markov chains for the structural parameters and volatilities and the matrices $B_1\left(\xi_t^{sp}\right)$, $A_1\left(\xi_t^{sp},\xi_{t+1}^{sp}\right)$, $B_2\left(\xi_t^{sp}\right)$, $C_1\left(\xi_t^{sp}\right)$ and $R\left(\xi_t^{sp}\right)$ are function of the model parameters.

As mentioned in the previous section, we introduce the possibility of regime change for two structural parameters (*sp*) and to shock volatilities(*vol*) through three independent Markov chains: $\boldsymbol{\xi_t^{ff}}$, $\xi_t^{mp}$ and $\xi_t^{vol}$, respectively. The three chains denote the unobserved regimes associated with market segmentation, $\boldsymbol{\psi_{n,\xi_t^{ff}}}$, monetary policy response to the term premium, $\tau_{tp,\xi_t^{mp}}$, and risk shock volatility, $\boldsymbol{\sigma_{\phi,\xi_t^{vol}}}$.

These processes could be subject to regime shifts. For the parameters, we assume that, if there are regime switches, they take on discrete values $i \in \{1,2\}$, where regime 1 implies high absolute values for market segmentation and monetary policy response to the term premium, and the opposite is true for low parameters. [8]

The two Markov chains for parameters are assumed to follow a first-order process with the following transition matrices, respectively:

$$H^i = \begin{pmatrix} H_{11} & H_{12} \\ H_{21} & H_{22} \end{pmatrix} \qquad for \quad i = ff,\ mp \tag{18}$$

where $H_{ab} = p(sp_t = b|sp_{t-1} = a)$, for $a, b = 1{,}2$. Then, $H_{ab}$ stands for the

[6] Based in perturbation methods as the approach presented by Barthélemy and Marx (20ll) and Foerster et al. (20l4).
[7] See McCallum (1983).
[8] The identification for each regime will be described in detail in sub-section 4.4.

probability of being in regime $b$ at $t$ given that the system was in regime $a$ at $t-1$.

The Markov chain for volatilities is assumed to follow a first-order process with the following transition matrix:

$$H = \begin{pmatrix} H_{11} & H_{12} & H_{13} \\ H_{21} & H_{22} & H_{23} \\ H_{31} & H_{32} & H_{33} \end{pmatrix} \tag{19}$$

where $H_{ab} = p(sp_t = b | sp_{t-1} = a)$, for $a, b = 1, 2, 3$, with the same interpretation for each $H_{ab}$ element.

Various authors have focused on the concept of mean square stability solutions[9] for 17. As is emphasized by Maih (2015) and Foerster (2016), this condition implies finite first and second moments in expectations for the system:

$$\lim_{j\to\infty} \mathbb{E}_t\left[X_{t+j}\right] = \bar{x} \tag{20}$$

$$\lim_{j\to\infty} \mathbb{E}_t\left[X_{t+j}X'_{t+j}\right] = \Sigma \tag{21}$$

To solve the system, we use the Newton methods developed in Maih (2015) which extend the one proposed by Farmer, Waggoner and Zha (2011) and concentrates in minimum state variable solutions of the form:

$$X_t = \Omega^*(\xi^{sp}, \theta^{sp}, H)X_{t-1} + \Gamma^*(\xi^{sp}, \theta^{sp}, H)Z_t(\xi^{vo}, \theta^{vo}) \tag{22}$$

Finally, to complete the state form of the model, 17 is combined with the measurement Equation 23:

$$Y_t^{obs} = MX_t \tag{23}$$

where $Y_t^{obs}$ are the observables.

## 4.2 MS-DSGE Model Estimation Methods

The standard Kalman filter cannot be used to compute the likelihood, because of the presence of unobserved states of the Markov chains, the filtering inferences must be conditioned on information of the current and past state of the system, $s_t$ and $s_{t-1}$, respectively. If the filter considers all the possible paths of the system, in each iteration, these will be multiplied by the number of possible regimes, $h$. In a few numbers of steps, the number of paths of the systems would increase making the computation of the problem infeasible as pointed by Alstadheim et al. (2013). To make treatable this problem, Kim and Nelson (1999) propose an approximation that averages across

[9] See Costa et al. (2006); Cho (2014); Foerster et al. (2014); Maih (2015).

states.[10] Following the approach outlined in Alstadheim et al. (2013) and Bjørnland et al. (2018), an averaging operation (collapse) is applied during the filtering procedure. This form of calculation has computational savings and similar numeric results to the Kim-Nelson approach (Kim and Nelson, 1999; Bjørnland et al., 2018).

This paper uses the Bayesian approach to estimate the model with the following procedure:

*1)* We compute the solution of the system using an algorithm found in Maih (2015) and employ a modified version of the Kim and Nelson (1999) filter to compute the likelihood with the prior distribution of the parameters.

*2)* Construct the posterior kernel result from stochastic search optimization routines.[11]

*3)* We use the mode of the posterior distribution as the initial value for a Metropolis-Hasting algorithm,[12] with 50,000 iterations, to construct the full posterior distribution.

*4)* Utilizing mean and variance of the last 40,000 iterations from *3)*, we run the main Metropolis Hastings algorithm to compute moments.

### 4.3 Database

We use US data from 1962Q1 to 2017Q3 for the estimation of the model. The database takes the original series reported in Carlstrom et al. (2017) but extend the sample from 2008Q4 to 2017Q3. Quarterly series were selected for the annualized growth rates of real GDP, real gross private domestic investment, real wages, inflation rate–personal consumption expenditure index– and real wages.[13] The labor input series was constructed substituting the trend component from the nonfarm business sector (hours of all persons) series. The series for the federal funds rate is obtained averaging monthly figures downloaded from the Federal Reserve Bank of St. Louis’s website. Additionally, for the term premium, we take the Treasury term premia series from the Federal Reserve Bank of New York’s website, estimated by Adrian et al. (2013). All data are demeaned. Series are presented in Annex 1.

[10] This algorithm involves running the Kalman-filter for each of the paths and taking a weighted average using the weights given by the probability assigned to each path from the filter proposed in Hamilton (l989).
[11] Provided in the RISE toolbox.
[12] With an acceptance ratio of $\alpha = 0.28$.
[13] Defined as nominal compensation in the nonfarm business sector divided by the consumption deflator.

### 4.4 Prior Specification

Following Carlstrom et al. (2017), we calibrate several parameters to match the long-run features of the US data, which are reported in Table 2. Regarding the non-switching block of parameters in the model, following Bjørnland et al. (2018), rather than setting means and standard deviations for the prior densities, these are set using quantiles of the distributions. Specifically, we use 90% probability intervals of the respective distribution to uncover the underlying hyperparameters, based on the results reported by Carlstrom et al. (2017). The choice of prior distributions for the constant and switching parameters are displayed in the right panel of Tables 5 and 6, respectively.

For identification purposes, we characterized the high financial market segmentation regime, $\xi_t^{ff} = 1$, to be a regime where credit market present high portfolio adjustment cost (that is, $\psi_{n,\xi_t^{ff}=1} > \psi_{n,\xi_t^{ff}=2}$). Meanwhile, for regime changes in the monetary policy's response to term premium, we define, $\xi_t^{mp} = 1$, to be the regime where the Central Bank responds strongly to changes in this variable (i.e. $\left|\tau_{tp,\xi_t^{mp}=1}\right| > \left|\tau_{tp,\xi_t^{mp}=2}\right|$). The model also allows for regime switching in the shocks; thus, we let the risk volatility shock follow an independent three-state Markov-process. Then, we indicate the high, medium and low volatility regimes, $\xi_t^{vol} = 1$, $\xi_t^{vol} = 2$ and $\xi_t^{vol} = 3$, respectively, which implies the following non-linear restriction: $\sigma_{\phi,\xi_t^{vol}=1} > \sigma_{\phi,\xi_t^{vol}=2} > \sigma_{\phi,\xi_t^{vol}=3}$.

*Table 2: Calibrated Parameters*

| Parameter | value |
|---|---|
| $\beta$ | 0.99 |
| $\alpha$ | 0.33 |
| $\delta$ | 0.025 |
| $\rho_{r_t^{10}}$ | 0.85 |
| $\epsilon_p = \epsilon_w$ | 5 |
| $L_{ss}$ | 6 |
| $s$ | 0.01 |
| $R_{ss}^L$ | $1/\beta$ |
| $(1-\kappa)^{-1}$ | 40 |

## 5. DSGE vs MS-DSGE ESTIMATION RESULTS COMPARISON

### 5.1 MS Evidence of Switching Coefficients and/or Switching Variance

To determine if the data favors a Markov-switching DSGE specification with changes in structural parameters and/or shock volatilities relative to a time- invariant DSGE model, we compare the goodness-of-fit of alternative models. To differentiate the models, we label them as $\#_S S \#_R R \#_V V$, where $\#_S = 1, 2$ denotes the number of possible regime of the financial market segmentation parameter $\boldsymbol{\psi}_{\boldsymbol{n},\boldsymbol{\xi}_t^{ff}}$, $\#_R = 1, 2$ denotes the number of possible regimes of the monetary policy's interest rate response to the term premium parameter $\tau_{tp,\xi_t^{mp}}$, and $\#_V = 1, 2, 3$ denotes the number of possible regimes of risk volatility shock $\boldsymbol{\sigma}_{\phi,\xi_t^{vol}}$. Then, a model labeled as 1S1R1V corresponds to the time-invariant Gaussian DSGE model, while 2S2R3V has two regimes in financial market segmentation, two regimes of monetary policy's interest rate response to the term premium, and three regimes of risk volatility shock.

Table 3 displays the comparison of 12 specifications, where models' goodness-of-fit are compared by the Marginal Likelihood. As in the MS-VAR comparison, in this MS-DSGE comparison, all the specifications allowing for regime switch are preferred to the constant model version. Allowing for a second regime of risk volatility shock provides the greatest fit improvement, followed by allowing a second regime in financial market segmentation, then by allowing a second regime in the interest rate response to the term premium, and lastly, but still significantly important when allowing for a third regime of risk volatility shock. The model with the best fit to the data is 2S2R3V, which is the model we will use in Section 6 to perform counterfactual exercises.

Table 3 also reports the posterior mode for the estimated parameters. Note that, for comparable specifications, when Markov-switching is allowed, the estimated parameters take into smaller and larger values than the middle level values of the comparable parameters-invariant version. For example, in the constant parameters' specification, 1S1R1V, the estimated parameters are $\boldsymbol{\psi}_{\boldsymbol{n}} = 0.89$, $\tau_{tp} = -0.46$, and $\boldsymbol{\sigma}_{\phi,\xi_t^{vol}} = 4.01$. Meanwhile, in the model with regime switching in credit market segmentation, 2S1R1V, the estimated high financial market segmentation regime is $\boldsymbol{\psi}_{\boldsymbol{n},\boldsymbol{\xi}_t^{ff}=\mathbf{1}} = 1.49$, while the one for the low segmentation regime is $\boldsymbol{\psi}_{\boldsymbol{n},\boldsymbol{\xi}_t^{ff}=\mathbf{2}} = 0.69$. In the case of the model with regime switching in the risk volatility shock, 1S1R2V, the estimated high volatility regime is $\boldsymbol{\sigma}_{\phi,\xi_t^{vol}=1} = 7.01$, while the low volatility regime is $\boldsymbol{\sigma}_{\phi,\xi_t^{vol}=2} = 2.99$.

*Table 3: DSGE and MS-DSGE Estimation Results.*

| # of Markov chains | # of States | Specifica tion | Marginal Likeliho ods | Market segmentation | | Term premium response | | Credit shock volatility | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | $\psi_{n,\xi_t^{ff}=1}$ | $\psi_{n,\xi_t^{ff}=2}$ | $\tau_{tp,\xi_t^{mp}=1}$ | $\tau_{tp,\xi_t^{mp}=2}$ | $\sigma_{\phi,\xi_t^{vol}=1}$ | $\sigma_{\phi,\xi_t^{vol}=2}$ | $\sigma_{\phi,\xi_t^{vol}=3}$ |
| | | | | Density: Uniform | | Density: Normal | | Density: Inverse Gamma | | |
| 1 | 1 | 1S1R1V | -2985.05 | 0.89 | - | -0.46 | - | 4.01 | - | - |
| 2 | 2 | 1S1R2V | -2,601.51 | 0.84 | - | -0.49 | - | 7.01 | 2.99 | - |
| 2 | 3 | 1S1R3V | -2,599.17 | 0.59 | - | -0.52 | - | 6.98 | 5.35 | 2.78 |
| 2 | 2 | 2S1R1V | -2,714.86 | 1.49 | 0.69 | -0.84 | - | 6.04 | - | - |
| 3 | 4 | 2S1R2V | -2,544.11 | 0.97 | 0.36 | -0.50 | - | 6.40 | 2.61 | - |
| 3 | 6 | 2S1R3V | -2,548.58 | 0.65 | 0.19 | -0.50 | - | 6.72 | 5.31 | 3.09 |
| 2 | 2 | 1S2R1V | -2,757.08 | 0.81 | - | -0.97 | -0.52 | 6.29 | - | - |
| 3 | 4 | 1S2R2V | -2,577.19 | 0.68 | - | -0.82 | -0.24 | 6.53 | 3.05 | - |
| 3 | 6 | 1S2R3V | -2,567.76 | 0.66 | - | -0.96 | -0.38 | 6.56 | 5.33 | 2.69 |
| 3 | 4 | 2S2R1V | -2,701.63 | 1.39 | 0.63 | -1.10 | -0.46 | 5.74 | - | - |
| 4 | 8 | 2S2R2V | -2,538.06 | 0.91 | 0.25 | -0.90 | -0.30 | 6.27 | 3.19 | - |
| 4 | 12 | 2S2R3V | -2,530.12 | 0.90 | 0.22 | -0.86 | -0.30 | 6.87 | 6.13 | 3.01 |

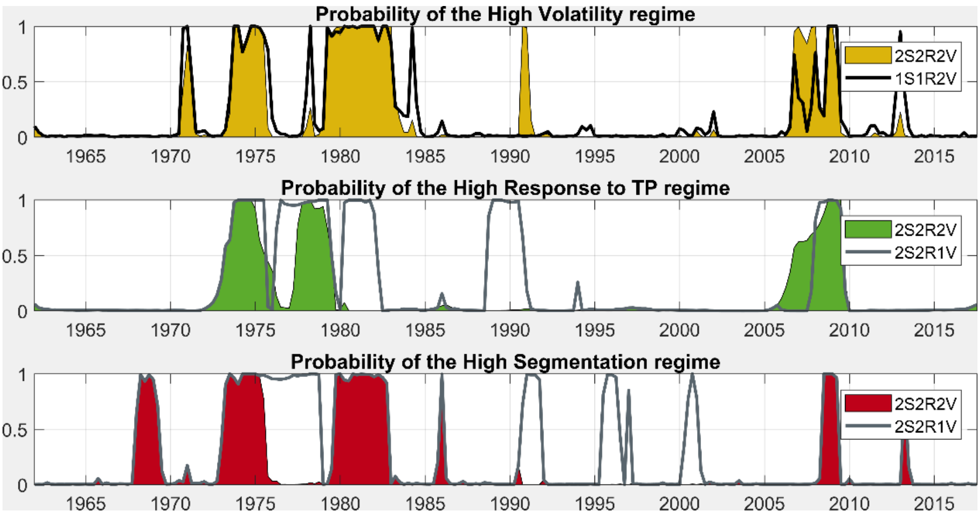
*Note. The table reports the Marginal Data Densities for the estimated models. In the column Specification, S, R and V correspond to segmentation, interest rate and volatilities, respectively. The posterior mode is reported for all the parameters.*

## 5.2 Regime Probabilities

To illustrate the effects of restricting Markov Switching in parameters and/or volatilities, Figure 4 presents a comparison of the estimated regime probabilities of the MS-DSGE models at the posterior mode for the versions 2S2R2V versus 1S1R2V and 2S2R1V. Annex 5 shows the comparisons of the version 2S2R2V versus the following specifications: 1S2R2V, 2S1R2V, 2S2R1V, and the model with the best fit 2S2R3V. In addition, Annex 5 also shows the comparison of version 2S1R2V versus 1S1R2V, 2S1R1V and 2S1R3V.

First, recall from Table 3 that the Marginal Likelihoods of model 2S2R2V = -2,538.06, which represents a better fit than the model 1S1R2V = 2,601.51 and the model 2S2R1V = -2701.63. Now, from the top panel of Figure 4, which depicts the probability of a high volatility regime, we observe that when parameters are not allowed to switch as in 1S1R2V, the estimation could interpret that an event is of high volatility, when it is otherwise one in which structural parameters are switching as in 1979, 1984 and 2013. Likewise, as can be observed in the middle and bottom panels, when shock volatilities are not allowed to switch as in 2S2R1V, the estimation could interpret that an event corresponds to a parameter switch, when it seems likely to be a shock volatility switch. For example, in the middle panel, the 2S2R1V model captures episodes in 1977, 1980 – 1982, and 1989 – 1990 as ones in which the monetary policy was highly responsive to the term premium, while the 2S2R2V model has either high volatility and/or high financial market segmentation. Something parallel happens in the bottom panel, when comparing models 2S2R2V and 2S2R1V, on which by restricting the shock volatility regime there are several episodes identified in 2S2R1V as high financial market segmentation, as 1975 – 1980, 1990, 1995 and 2000, that do not coincide with the estimation in the 2S2R2V model.

*Figure 4. Comparison of the Estimated Regime Probabilities of the MS-DSGE Models at the Posterior Mode 2S2R2V vs 1S1R2V and 2S2R1V*




*Note: The top panel depicts the probability of the high volatility regime; the medium panel, the probability of the high response to term premium regime; and the bottom panel, the probability of the high segmentation regime.*

*Table 4: Model Comparisons of the 2S2R2V Model versus the 1S1R2V Model and the 2S2R1V Model.*

| **Model:** | **2S2R2V** | | | **1S1R2V** | **2S2R1V** | |
|---|---|---|---|---|---|---|
| **Switching on:** | **S** | **R** | **V** | **V** | **S** | **R** |
| **# periods probability > 50%:** | 35 | 31 | 37 | 36 | 61 | 48 |
| **% of total sample** | 16% | 14% | 17% | 16% | 27% | 22% |
| **Models to be compared:** | | | | **2S2R2V vs 1S1R2V** | **2S2R2V vs 2S2R1V** | |
| **Switching on:** | | | | **V** | **S** | **R** |
| **# of periods when probability > 50% in both models:** | | | | 31 | 35 | 26 |
| **% of 112 or 221:** | | | | 86% | 57% | 54% |

*Note. The table reports the number of periods in which each model assigns high probabilities of a high financial market segmentation (S), high monetary policy interest rate response to the term premium (R), and high financial shock volatility regime (V). It also reports the number of periods in which the identification coincides in the two compared models.*

A complementary way to compare these 3 models, 2S2R2V versus 1S1R2V and 2S2R1V is to analyze the number of periods (quarters) in which the estimation assigns a high probability (here define as more than 50% probability) of: the high segmentation regime (S), the high monetary policy interest rate response to term premium regime (R), and the high financial shock volatility regime (V), as corresponds. Table 4 shows that Model 2S2R2V identifies 35, 31 and 37 periods as high S, high R and high V, respectively. Model 1S1R2V identifies 36 periods as high V. When compared 2S2R2V with 1S1R2V, we see that 31 of those periods are considered as high V by both models. Meanwhile, model 2S2R1V identifies 61 periods as high S and 48 periods as high R, a large overidentification. Therefore, by restricting the MS in volatilities there is a magnification of the identified regime switches in parameters.

To further complement the evidence, Figure 5 shows the estimated monetary policy shocks, $\sigma_{mp}$, with and without Markov Switching by comparing model 2S2R2V versus 1S1R1V and shows the probability of high monetary policy interest rate response to the term premium, $\tau_{tp,\xi_t^{mp}=1}$. We observe that during 1974, in the aftermath of the Oil Embargo, there is a high probability of a high monetary policy response, which in the 1S1R1V model is lumped into more volatile monetary policy shocks. Something similar happens during the 2008 Global Financial Crisis.

*Figure 5. Monetary policy shocks with and without regime switching (2S2R2V vs 1S1R1V) and probability of high monetary policy interest rate response to the term premium*

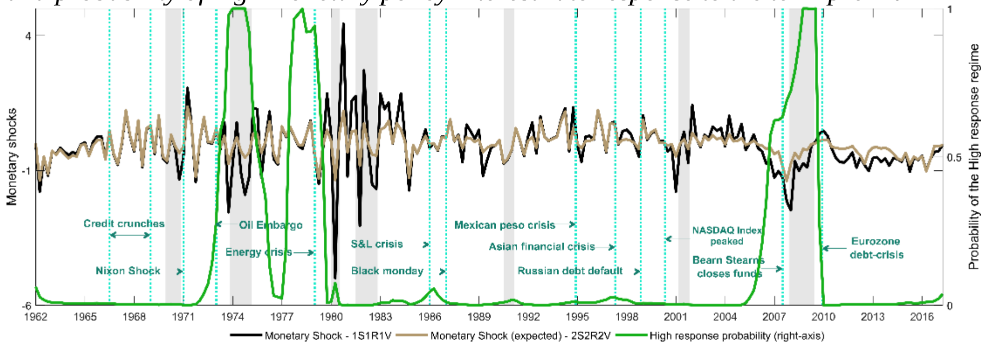



Figure 6 shows the estimated credit shocks, $\sigma_{\phi}$, with and without Markov Switching by comparing model 2S2R2V versus 1S1R1V and shows the probability of high financial market segmentation, $\boldsymbol{\psi}_{n,\xi_t^{ff}=1}$. We also observe that in the model without Regime Switching, some relevant episodes of high credit frictions are accommodated with larger credit shocks, as those around 1968 credit crunches, the 1973 – 1974 Oil Embargo, the 1980 – 1982 Energy and Emerging Countries; Sovereign Debt Crises, the 1986 Savings and Loans Crisis, the 2008 Global Financial Crisis, and 2013.

*Figure 6. Credit shocks with and without regime switching (2S2R2V vs 1S1R1V) and probability of high credit frictions*

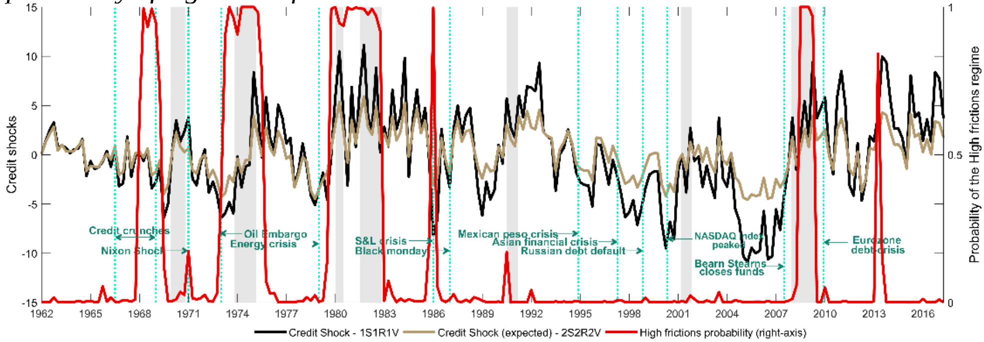
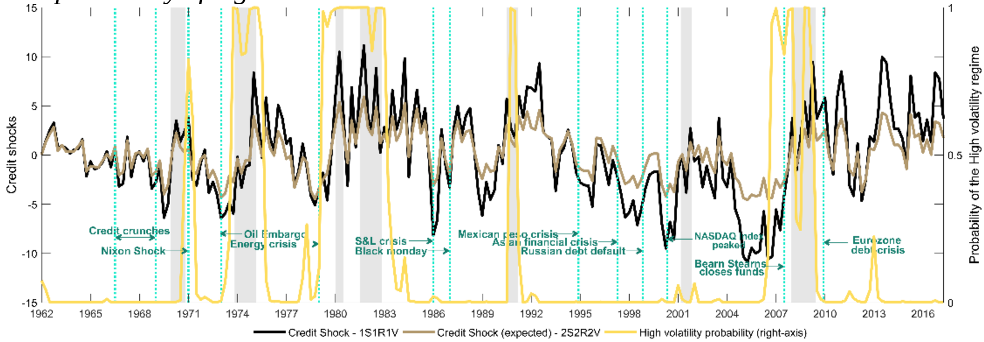



Figure 7 shows the estimated credit shocks, $\sigma_{\phi}$, with and without Markov Switching by comparing model 2S2R2V versus 1S1R1V and shows the probability of high-risk volatility shock $\sigma_{\phi,\xi_t^{vol}=1}$. The first thing to note is that when allowing for Markov-Switching parameters the variability of the shocks is smaller. In addition, the estimation assigns a high probability of the high volatility regime around most of the NBER identified recessions, when the Dot-com Bubble Burst followed by the War in Afghanistan.

*Figure 7. Credit shocks with and without regime switching (2S2R2V vs 1S1R1V) and probability of high credit shocks*



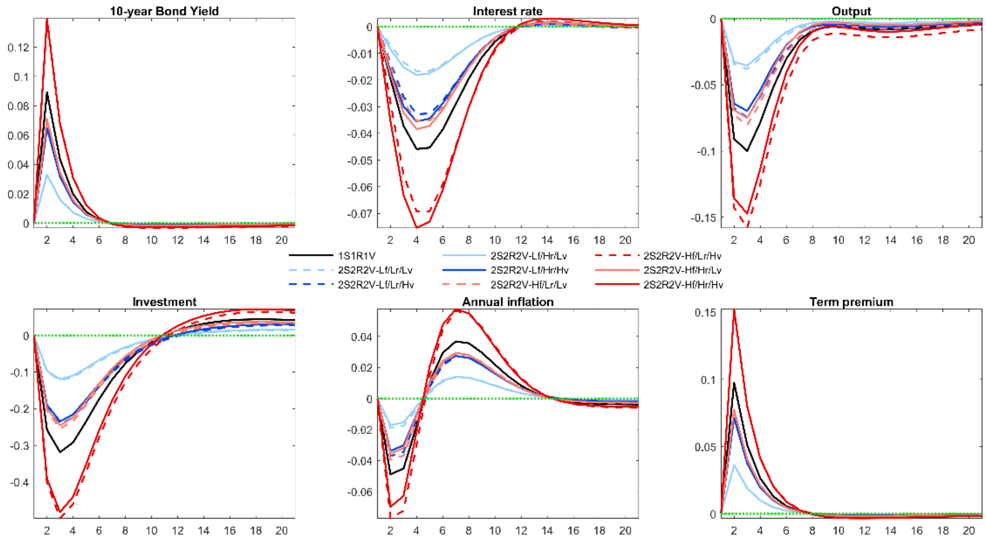

The evidence in this section illustrates that when Markov Switching in parameters and/or shocks volatilities are restricted, the estimation of a DSGE will be accommodated through average parameter estimates, not capturing for different regimes present in the economy, and/or through more volatile shocks.

### 5.3 Impulse Response Functions

This subsection presents the impulse response functions in response to a one-standard deviation shock to credit, $\sigma_{\phi}$, and monetary policy, $\sigma_{mp}$, for the 1S1R1V model and the 2S2R2V model. Note that the 1S1R1V model has only one IRF curve, while the 2S2R2V model has eight IRF curves as there are 2x2x2 combinations.

Figure 8 shows the impulse response functions of selected variables to a one-standard deviation credit shock, $\sigma_{\phi}$. An unexpected increase of the credit shock increases the 10-year bond yield and the term premium. The costlier financing causes a drop in investment and output. Inflation initially decreases. With lower output and lower inflation, interest rates decreases. The lower interest rate eventually generates inflation. Keeping everything else constant, the effect of this shock on the term premium is larger if the economy is in a high financial friction regime (reds) relative to a low financial friction regime (blues). Also, with the exception of nominal interest rates, the effects are larger if there is low interest rate response (dashed), relative to a high interest rate response (solids). Obviously, the larger the volatility of the shock (darkest), the greater the amplification of the responses. Notice that the IRFs dynamics for these two models 1S1R1V vs 2S2R2V are similar, but the magnitudes are different depending on the regimes the economy is at.

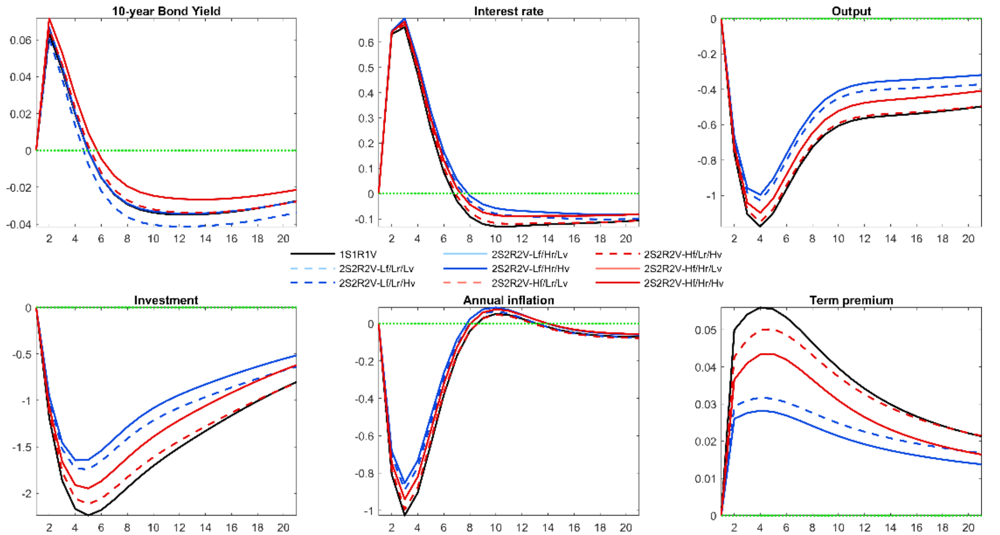
*Figure 8. Impulse Response Functions to a Credit Shock*




*Note: IRFs of the MS-DSGE model to a one standard deviation credit shock under alternative regimes for financial frictions, monetary policy and volatility. High financial frictions regimes are presented in red-like colors, while low ones are presented in blue-like colors. High monetary policy response regimes are presented in solid lines, while low ones are presented in dashed lines. High volatility regimes have dark colors, while low ones are presented in light ones.*

Figure 9 shows the impulse response functions of selected variables to a one-standard deviation monetary policy shock, $\sigma_{mp}$. The unexpected increase lowers investment, output, and inflation, with larger drops when monetary policy has a low term premium interest rate elasticity (dashed). The term premium increase is higher when there are financial frictions (reds) and when interest rate response is low (dashed).

*Figure 9. Impulse Response Functions to a Monetary Shock*




*Note: IRFs of the MS-DSGE model to a one standard deviation monetary policy shock under alternative regimes for financial frictions, monetary policy and volatility. High financial frictions regimes are presented in red-like colors, while low ones are presented in blue-like colors. High monetary policy response regimes are presented in solid lines, while low ones are presented in dashed lines. High volatility regimes have dark colors, while low ones are presented in light ones.*

# 6. MS-DSGE ESTIMATION RESULTS OF 2S2R3V MODEL

## 6.1 Parameter Estimation of the 2S2R3V MS-DSGE Model

In this section, we report the posterior parameter estimates. The Bayesian estimation uses the posterior mode as initial value. Table 5 reports the estimates of the constant parameters, while Table 6 reports the estimates of the switching parameters, shocks standard deviations, and elements of the transition matrices. We focus our discussion on the results of the switching elements.

The first thing to notice is that there are big differences in the parameter that characterizes the financial frictions related to the financial intermediaries' hold-up problem. Remember that if $\psi_n = 0$, the supply of credit is perfectly elastic, independent of the financial intermediaries' net worth, while as $\psi_n$ becomes larger, the financial friction becomes more intense, and the supply of credit depends positively on the financial intermediaries' net worth. As is shown later in Figures 10 and 11, the high financial frictions regime, with $\boldsymbol{\psi_{n,\xi_t^{ff}=1} = 1.98}$, gives an important role to financial factors into the macroeconomic determination; while the low financial frictions regime, with $\boldsymbol{\psi_{n,\xi_t^{ff}=2} = 0.11}$, is close to a frictionless case, where financial factors do not determine macroeconomic outcomes. The transition matrix has a relatively high probability of regime switching with a $H_{1,2}^{ff} = 21\%$ probability of moving from high to low financial frictions and $H_{2,1}^{ff} = 20\%$ probability of moving from a low to a high financial frictions' regime.

*Table 5: Posterior Means, Modes, and 90% Probability Intervals, and Prior Probability Intervals of the Constant-Block Parameters*

| Constant parameters | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Parameter | Density | Posterior | | | | Prior | | |
| | | Mean | Mode | 10% | 90% | Mode | 10% | 90% |
| $\eta$ | *Gamma* | 1.4324 | 1.4633 | 1.1024 | 1.7624 | 2.0259 | 1.2673 | 2.7526 |
| $h$ | *Beta* | 0.6890 | 0.7014 | 0.6367 | 0.7412 | 0.6225 | 0.5760 | 0.6687 |
| $\psi_i$ | *Gamma* | 3.4380 | 3.2967 | 2.9914 | 3.8846 | 3.2821 | 2.1857 | 4.3639 |
| $\iota_p$ | *Beta* | 0.4118 | 0.4201 | 0.2103 | 0.6133 | 0.4172 | 0.2752 | 0.5610 |
| $\iota_w$ | *Beta* | 0.5109 | 0.5157 | 0.39871 | 0.6231 | 0.5110 | 0.4085 | 0.6205 |
| $\kappa_{pc}$ | *Beta* | 0.1000 | 0.0966 | 0.00135 | 0.1986 | 0.0860 | 0.0104 | 0.1544 |
| $\kappa_w$ | *Beta* | 0.0057 | 0.0054 | 0.00201 | 0.0093 | 0.0002 | 0.0001 | 0.0004 |
| $\rho_a$ | *Beta* | 0.9659 | 0.9412 | 0.9421 | 0.9898 | 0.9921 | 0.9841 | 0.9997 |
| $\rho_\mu$ | *Beta* | 0.8483 | 0.8364 | 0.7853 | 0.9112 | 0.8695 | 0.8281 | 0.9122 |
| $\rho_\phi$ | *Beta* | 0.9919 | 0.9871 | 0.9878 | 0.9960 | 0.9821 | 0.9682 | 0.9963 |
| $\rho_{mk}$ | *Beta* | 0.5312 | 0.5501 | 0.4302 | 0.6322 | 0.6650 | 0.4945 | 0.8405 |
| $\rho_w$ | *Beta* | 0.3798 | 0.3706 | 0.3556 | 0.4039 | 0.2059 | 0.1036 | 0.3027 |
| $\rho_m$ | *Beta* | 0.2240 | 0.2503 | 0.0516 | 0.3963 | 0.1564 | 0.0646 | 0.2515 |
| $\rho_{rn}$ | *Beta* | 0.9126 | 0.9361 | 0.93164 | 0.9936 | 0.9483 | 0.9212 | 0.9751 |

Regarding monetary policy, when it responds strongly to the term premium, $\xi_t^{mp} = 1$, the posterior mean of the policy rule is: $ln(R_t) = 0.65ln(R_{t-1}) + (1 - 0.65)\left(1.37\pi_t + 0.13y_t^{gap} - 1.16\,\tau_{tp,\xi_t^{mp}} tp_t\right)$; meanwhile, for the low response regime, $\xi_t^{mp} = 2$ we have: $ln(R_t) = 0.80ln(R_{t-1}) + (1 - 0.80)\left(1.75\pi_t + 0.08y_t^{gap} - 0.24\,\tau_{tp,\xi_t^{mp}} tp_t\right)$

As shown in Figures 10 and 11, the model dynamics are different as the central bank's response to the term premium is more aggressive. The policy rules exhibit important differences across regimes in the persistence of interest rates and the relative weights on inflation and output gap. The transition matrix has a relatively low probability of regime switching with a $H_{1,2}^{mp} = 9\%$ probability of moving from high to low interest rate response to the term premium and only $H_{2,1}^{mp} = 4\%$ probability of moving from a low to a high interest rate response regime.

The standard deviations of the seven shocks included in the model can change across regimes. High, medium, and low volatility regimes are classified by the size of the standard deviation $\sigma_{\phi,\xi_t^{vol}}$ of the credit shocks $\varepsilon_{\phi,t}$. Remember that this shock, by increasing the interest rate spread, lowers real activity. It is noticeable that for the seven shocks the 90% confidence intervals of the high volatility regimes are larger than those of medium volatility regimes, which in turn are larger than those of low volatility regimes.[14] The probabilities of exiting a high volatility regime are $H_{1,2}^{vol} = 1\%$ to medium

[14] The only exceptions are the 90% confidence intervals for the medium and low volatility regimes

*Table 6: Posterior Means, Modes, and 90% Probability Intervals, and Prior Means and Standard Deviations of the Switching-Block Parameters*

| Switching parameters, variances and transition matrices | | | | | | | |
|---|---|---|---|---|---|---|---|
| Parameter | Density | Posterior | | | | Prior | |
| | | Mean | Mode | 10% | 90% | Mean | Std. dev. |
| $\psi_{n,\xi_t^{ff}=1}$ | *Uniform* | 1.9778 | 1.9928 | 1.6412 | 2.3143 | 1 | 0.5 |
| $\psi_{n,\xi_t^{ff}=2}$ | *Uniform* | 0.1060 | 0.0870 | 0.0124 | 0.1996 | 1 | 0.5 |
| $\tau_{tp,\xi_t^{mp}=1}$ | *Normal* | -1.1597 | -1.2100 | -1.2280 | -1.0914 | -1 | 0.5 |
| $\tau_{tp,\xi_t^{mp}=2}$ | *Normal* | -0.2395 | -0.3352 | -0.3564 | -0.1226 | -0.5 | 0.5 |
| $\rho_{R,\xi_t^{mp}=1}$ | *Beta* | 0.65065 | 0.8016 | 0.5401 | 0.7612 | 0.5 | 0.3 |
| $\rho_{R,\xi_t^{mp}=2}$ | *Beta* | 0.79565 | 0.8016 | 0.7401 | 0.8512 | 0.5 | 0.3 |
| $\tau_{\pi,\xi_t^{mp}=1}$ | *Normal* | 1.3659 | 1.2864 | 1.2813 | 1.4505 | 1.5 | 0.5 |
| $\tau_{\pi,\xi_t^{mp}=2}$ | *Normal* | 1.7504 | 1.6697 | 1.6532 | 1.8477 | 1.5 | 0.5 |
| $\tau_{y,\xi_t^{mp}=1}$ | *Normal* | 0.1330 | 0.1276 | 0.1123 | 0.1538 | 0.5 | 0.3 |
| $\tau_{y,\xi_t^{mp}=2}$ | *Normal* | 0.0778 | 0.0771 | 0.0635 | 0.0921 | 0.5 | 0.3 |
| $\sigma_{\phi,\xi_t^{vol}=1}$ | *Inv. Gamma* | 7.5666 | 7.5643 | 6.1589 | 8.9712 | 0.5 | 1 |
| $\sigma_{\phi,\xi_t^{vol}=2}$ | *Inv. Gamma* | 4.0118 | 4.1237 | 3.1283 | 4.8953 | 0.5 | 1 |
| $\sigma_{\phi,\xi_t^{vol}=3}$ | *Inv. Gamma* | 3.8361 | 3.8928 | 3.0082 | 4.6640 | 0.5 | 1 |
| $\sigma_{a,\xi_t^{vol}=1}$ | *Inv. Gamma* | 0.78675 | 0.8025 | 0.7581 | 0.8154 | 0.5 | 1 |
| $\sigma_{a,\xi_t^{vol}=2}$ | *Inv. Gamma* | 0.6029 | 0.6087 | 0.5664 | 0.6394 | 0.5 | 1 |
| $\sigma_{a,\xi_t^{vol}=3}$ | *Inv. Gamma* | 0.44625 | 0.4314 | 0.3733 | 0.5192 | 0.5 | 1 |
| $\sigma_{\mu,\xi_t^{vol}=1}$ | *Inv. Gamma* | 7.63225 | 7.6133 | 7.6041 | 7.6604 | 0.5 | 1 |
| $\sigma_{\mu,\xi_t^{vol}=2}$ | *Inv. Gamma* | 4.3343 | 4.2359 | 4.0826 | 4.586 | 0.5 | 1 |
| $\sigma_{\mu,\xi_t^{vol}=3}$ | *Inv. Gamma* | 2.16765 | 2.1365 | 2.0281 | 2.3072 | 0.5 | 1 |
| $\sigma_{mp,\xi_t^{vol}=1}$ | *Inv. Gamma* | 0.46385 | 0.3254 | 0.2815 | 0.6462 | 0.5 | 1 |
| $\sigma_{mp,\xi_t^{vol}=2}$ | *Inv. Gamma* | 0.1371 | 0.1282 | 0.0953 | 0.1789 | 0.5 | 1 |
| $\sigma_{mp,\xi_t^{vol}=3}$ | *Inv. Gamma* | 0.10995 | 0.1088 | 0.0944 | 0.1255 | 0.5 | 1 |
| $\sigma_{mk,\xi_t^{vol}=1}$ | *Inv. Gamma* | 0.41 | 0.4068 | 0.3741 | 0.4459 | 0.5 | 1 |
| $\sigma_{mk,\xi_t^{vol}=2}$ | *Inv. Gamma* | 0.31185 | 0.3047 | 0.2826 | 0.3411 | 0.5 | 1 |
| $\sigma_{mk,\xi_t^{vol}=3}$ | *Inv. Gamma* | 0.2422 | 0.2389 | 0.2217 | 0.2627 | 0.5 | 1 |
| $\sigma_{w,\xi_t^{vol}=1}$ | *Inv. Gamma* | 1.1244 | 1.09 | 1.0818 | 1.167 | 0.5 | 1 |
| $\sigma_{w,\xi_t^{vol}=2}$ | *Inv. Gamma* | 0.50945 | 0.4953 | 0.4862 | 0.5327 | 0.5 | 1 |
| $\sigma_{w,\xi_t^{vol}=3}$ | *Inv. Gamma* | 0.4305 | 0.4257 | 0.3989 | 0.4621 | 0.5 | 1 |
| $\sigma_{rn,\xi_t^{vol}=1}$ | *Inv. Gamma* | 0.2338 | 0.2223 | 0.2146 | 0.253 | 0.5 | 1 |
| $\sigma_{rn,\xi_t^{vol}=2}$ | *Inv. Gamma* | 0.0838 | 0.0793 | 0.0723 | 0.0953 | 0.5 | 1 |
| $\sigma_{rn,\xi_t^{vol}=3}$ | *Inv. Gamma* | 0.0677 | 0.0635 | 0.0559 | 0.0795 | 0.5 | 1 |
| $H_{1,2}^{ff}$ | *Dirichlet* | 0.2072 | 0.2126 | 0.1803 | 0.2341 | 0.05 | 0.03 |
| $H_{2,1}^{ff}$ | *Dirichlet* | 0.2003 | 0.1974 | 0.1696 | 0.2310 | 0.05 | 0.03 |
| $H_{1,2}^{mp}$ | *Dirichlet* | 0.0850 | 0.0845 | 0.0719 | 0.0981 | 0.05 | 0.03 |
| $H_{2,1}^{mp}$ | *Dirichlet* | 0.0374 | 0.0443 | 0.0216 | 0.0532 | 0.05 | 0.03 |
| $H_{1,2}^{vol}$ | *Dirichlet* | 0.0144 | 0.0100 | 0.0053 | 0.0235 | 0.05 | 0.03 |
| $H_{1,3}^{vol}$ | *Dirichlet* | 0.0697 | 0.0660 | 0.0560 | 0.0833 | 0.05 | 0.03 |
| $H_{2,1}^{vol}$ | *Dirichlet* | 0.1719 | 0.1801 | 0.1528 | 0.1910 | 0.05 | 0.03 |
| $H_{2,3}^{vol}$ | *Dirichlet* | 0.1907 | 0.1803 | 0.1697 | 0.2117 | 0.05 | 0.03 |
| $H_{3,1}^{vol}$ | *Dirichlet* | 0.1728 | 0.1811 | 0.1459 | 0.1996 | 0.05 | 0.03 |
| $H_{3,2}^{vol}$ | *Dirichlet* | 0.1776 | 0.1816 | 0.1569 | 0.1982 | 0.05 | 0.03 |

*Note: The reported priors for Dirichlet distributions correspond to the resultant transition probabilities of the respective hyperparameters combination.*

for credit and monetary policy shocks, which exhibit some overlap, but the medium volatility means are larger than the low volatility ones.

volatility and $H_{1,3}^{vol} = 7\%$ to low volatility. The probabilities of exiting a medium volatility regime are $H_{2,1}^{vol} = 17\%$ to high volatility and $H_{2,3}^{vol} = 19\%$ to low volatility. Finally, the probabilities of exiting a low volatility regime are $H_{3,1}^{vol} = 17\%$ to high volatility and $H_{3,2}^{vol} = 18\%$ to medium volatility.

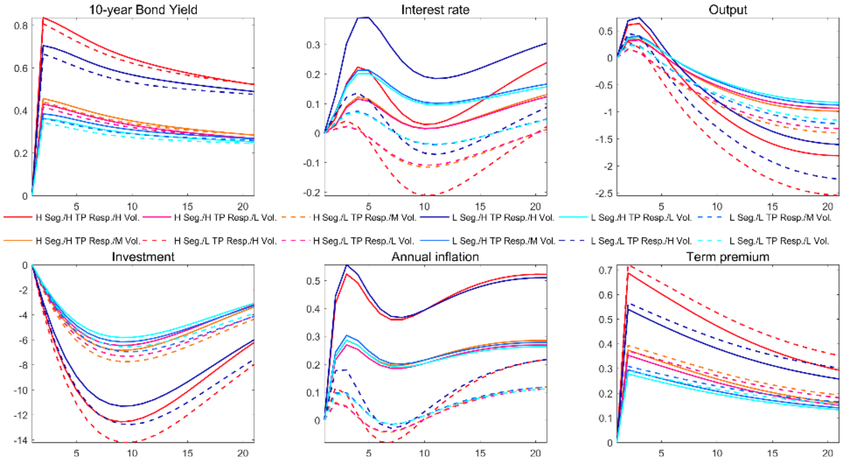
### 6.2 Impulse Response Functions of the 2S2R3V MS-DSGE Model

This subsection presents the impulse response functions in response to a one-standard deviation shock to credit, $\sigma_{\phi}$, and monetary policy, $\sigma_{mp}$. The impulse responses to a one-standard deviation shock to neutral technology, $\sigma_a$, investment-specific, $\sigma_{\mu}$, price markup, $\sigma_{mk}$, wage markup, $\sigma_w$, and intertemporal preference, $\sigma_{rn}$ are included in the Annex 5. Each graph has 12 lines which depict the responses under the two alternative financial friction (H Seg. and L Seg.), the two monetary policy response to term premium (H TP Resp. and L TP Resp.), and the three-credit-shock volatility (H Vol., M Vol., and L Vol.) regimes. High financial frictions regimes are presented in red-like colors, while low ones are presented in blue-like colors. High monetary policy response regimes are presented in solid lines, while low ones are presented in dashed lines. High volatility regimes have the darkest colors, medium mild tones, and low ones are in the lightest tones.

Figure 10 shows the impulse response functions of selected variables to a one-standard deviation credit shock. An unexpected increase of the credit shock increases the 10-year bond yield and the term premium. Keeping everything else constant, the effect of this shock on the term premium is larger if the economy is in a high financial friction regime (reds) or if the interest rate response to the term premium is low (dashed). The costlier financing causes a drop in investment, with the effect being larger under high financial frictions (reds) or low interest rate response (dashed). Despite the transitory increase in output, it eventually drops with the decline being larger under high financial frictions (reds) and low interest rate response (dashed). Inflation and nominal interest rates increase more under low financial frictions (blues) and high interest rate response (solids). Obviously, the larger the volatility of the shock (darkest), the greater the amplification of the responses.

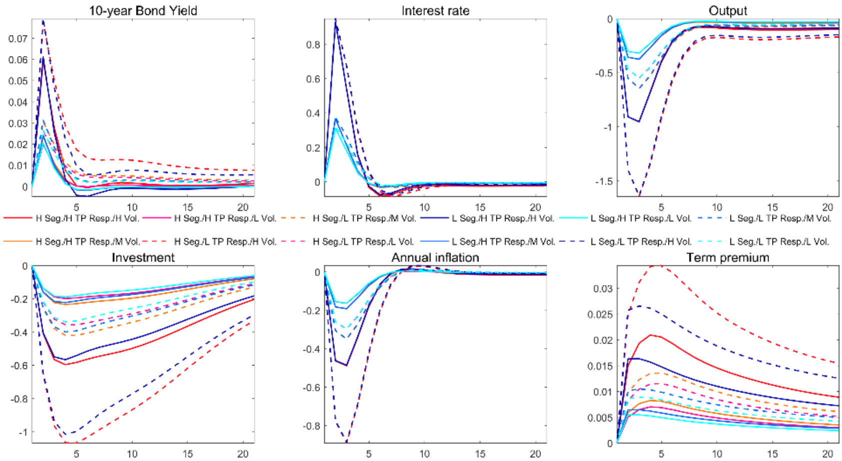
Figure 11 shows the impulse response functions of selected variables to a one-standard deviation monetary policy shock. The unexpected increase lowers investment, output, and inflation, with larger drops when monetary policy has a low term premium interest rate elasticity (dashed). The term premium increase is higher when there are financial frictions (reds) and when interest rate response is low (dashed).

*Figure 10 Impulse Response Functions of the 2S2R3V MS-DSGE Model to a One Standard Deviation Credit Shock Under Alternative Regimes for Financial Frictions, Monetary Policy and Volatility*




*Note: High financial frictions regimes are presented in red-like colors, while low ones are presented in blue-like colors. High monetary policy response regimes are presented in solid lines, while low ones are presented in dashed lines. High volatility regimes have the darkest colors, medium mild tones, and low ones are in the lightest tones.*

*Figure 11 Impulse Response Functions of the 2S2R3V MS-DSGE Model to a One Standard Deviation Monetary Policy Shock Under Alternative Regimes for Financial Frictions, Monetary Policy and Volatility*

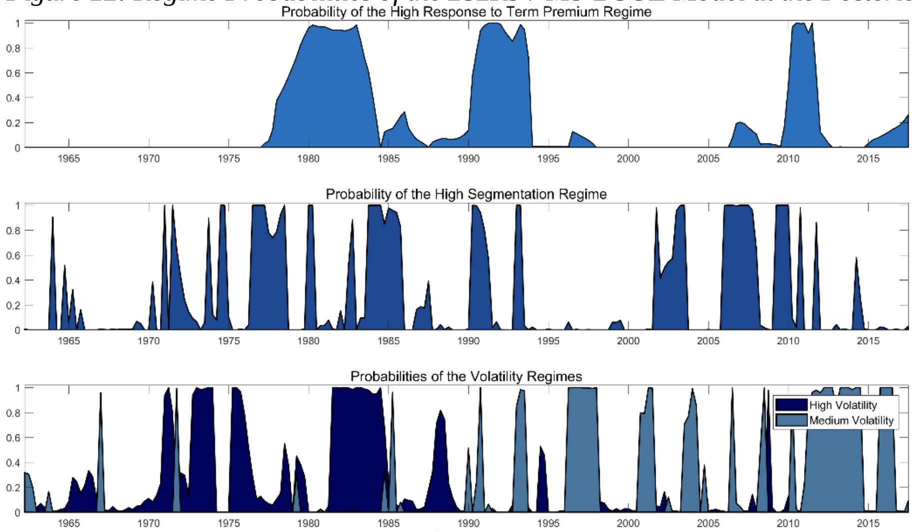



*Note: High financial frictions regimes are presented in red-like colors, while low ones are presented in blue-like colors. High monetary policy response regimes are presented in solid lines, while low ones are presented in dashed lines. High volatility regimes have the darkest colors, medium mild tones, and low ones are in the lightest tones.*

### 6.3 Regime Probabilities of the 2S2R3V MS-DSGE Model

The estimation provides us with the probabilities of high and low financial frictions and monetary policy response to the term premium regimes. Figure 12 shows the smoothed probabilities of each regime. The Bayesian maximum likelihood estimation of the MS-DSGE model identifies 59 quarters (27% of the sample that runs from 1962Q1 to 2017Q4) when financial frictions, measured by the financial intermediaries' portfolio adjustment costs to their net worth, had a large probability of being high with the following relevant intervals: 1971Q1-1971Q4, 1976Q3-1978Q3, 1983Q4-1985Q4, 1990Q2- 1991Q2, 2002Q3-2003Q3, 2006Q1-2008Q1, and 2009Q2-2010Q1.

*Figure 12: Regime Probabilities of the 2S2R3V MS-DSGE Model at the Posterior Mode*



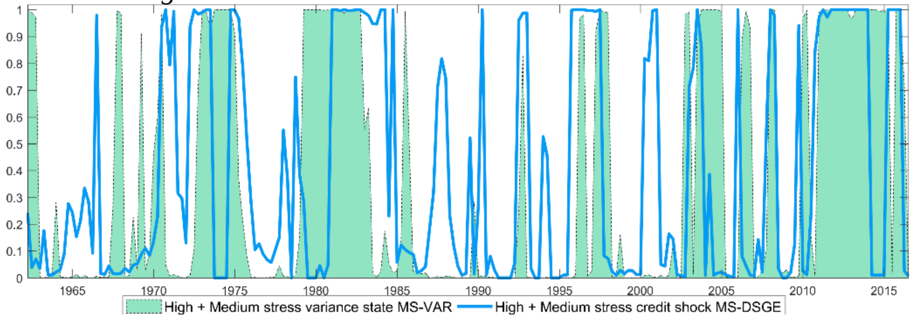

*Notes: The top panel depicts the probability of the high response to term premium regime; the middle panel, the probability of the high segmentation regime; and the bottom panel, the probabilities of the high and medium volatility regimes.*

Also, there are 43 quarters when the interest rate response to the term premium is estimated high with the following intervals: 1978Q4- 1983Q4, 1990Q2-1993Q4, and 2010Q1-2011Q4. In addition, the MS-DSGE model estimation has 34 quarters of large probability of high credit shock volatility, 46 quarters (20.6%) with large probability of medium credit shock volatility and 142 quarters (64%) with large probability of low credit shock volatility. In subsection 5.4 of counterfactual analysis, we provide a historical narrative of the most representative of these regime switching episodes.

Comparing the MS-VAR and MS-DSGE there are 17 quarters (8%) which are at the same time high-stress variance and high credit shock volatility, 24 quarters (11%) that are at the same time medium-stress variance and medium credit shock volatility, and 99 quarters (45%) that are identified both as low-stress variance and low credit shock volatility states. However, from Figure 13 the intersection of the two models yields 43 quarters (20%) that are identified at the same time both either medium or high-stress variance and medium and high credit shock volatility. These quarters are 1971Q1, 1973Q2-1974Q1, 1975Q2 and Q3, 1981Q3-1983Q4, 1993Q2, 1996Q4-1997Q1, 1997Q4-1981Q1, 2003Q3, 2004Q1 and Q2, 2008Q3 and Q4, 2011Q3-2014Q3, 2015Q4, and 2016Q2 and Q3.

In the next subsection we review the most relevant episodes.

*Figure 13: Comparison of 2c3v MS-VAR High and Medium Frictions States, and 2S2R3V MS-DSGE High and Medium Credit Shock Volatilities*




*Note: The green area reports the probabilities of the high and medium stress regime variance (as a sum) for the 2c3v MS-VAR model. The blue solid line reports the probabilities of the high and medium stress regime variance (as a sum) for the 2S2R3V MS-DSGE model.*

## 6.4 Counterfactual Analysis

To explore the characteristics of the MS-DSGE model with multiple parameters and variances regimes, in this exercise we generate counterfactual series based on conditional forecast simulations. Particularly, this analysis will permit us to have an idea of what could have happened if financial frictions, monetary policy regimes, and volatility regimes had remained constant, one at a time, in each of six selected episodes.

In what follows, we will examine two blocks of counterfactual simulation exercises when financial frictions and/or financial credit shocks were estimated as high or medium, which are shown chronologically in Figures 14-19. Figures 15, 16, and 18 corresponds to the three episodes in which the monetary policy posture was responsive to the term premium in the intervals 1978Q4-1983Q4, 1990Q2- 1993Q4, and 2010Q1-2011Q4, respectively. Meanwhile, Figures 14, 17, and 18 are three episodes in which the interest rate response to the term premium was low. These episodes correspond to the intervals: 1971Q1-1978Q3, 2000Q4-2004Q4, and 2006Q1-2009Q4, respectively. To complement the evidence, Table 8 reports the mean and standard deviation of each variable, in deviation from steady state, under the alternative counterfactuals for the analyzed episodes.

Counterfactual figures show alternative paths where only one feature of the regime switching can change, while keeping every- thing else constant. Red lines compare counterfactual according to the degree of financial frictions, red solid lines show the potential evolution of the variables under high credit market segmentation, while red dashed lines report potential evolution for the low financial frictions case.

Green lines compare counterfactual according to the monetary policy response to the term premium; green solid lines show the case of high policy response and green dashed lines of low reaction. Blue lines compare counterfactual under different degrees of credit shock volatility, blue solid lines are the hypothetical behavior under high volatility, blue dashed lines report the medium volatility case, and blue dotted lines report a scenario when low credit shock volatility had prevailed during the analyzed period. The solid black line is the data in deviation from steady state. Each figure presents four quarters before the regime switch, and conditions the fifth observation which corresponds to first quarter of the episode, say 1971Q1 or 1978Q4, to be the same and then let the conditional forecasts differ for each case, say high financial frictions while using other estimated transition matrices for monetary policy response and shocks volatility. In our attempt to determinate the role of each specific regime, we isolate the effects of the several sources of regime changes in the model.[15]

Since the start of our sample in 1962Q2 and until 1971Q1, the estimation assigns a high probability to a low credit market segmentation $\left[\psi_{n,\xi_t^{ff}=2} = 0.11\ (0.01, 0.20)\right]$ and low credit shock volatility $\left[\sigma_{\phi,\xi_t^{vol}=3} = 3.83\ (3.00, 4.67)\right]$ regime.[16] This despite the 1966 *credit crunch* and the Vietnam War expenses run by the government, the tighter monetary policy in 1967Q3 and 1968Q3, and that according to the NBER's Business Cycles Dating Committee there was an economic contraction from 1969Q4 to 1970Q4. During this period, the estimation assigns a high probability to a low interest rate response to the term premium $\left[\tau_{tp,\xi_t^{mp}=2} = -0.24\ (-0.36, -0.12)\right]$. Given that there is scant evidence of regime switching of either financial frictions, financial shocks or monetary policy response during this 1962Q2- 1971Q1 period, we do not perform a counterfactual exercise for it.

In contrast, in the 31 quarters running from 1971Q1 to 1978Q3, our estimation identifies 15 quarters with a high probability of credit market segmentation $\left[\psi_{n,\xi_t^{ff}=1} = 1.98\ (1.64, 2.31)\right]$ and 14 quarters of high probability of high credit shock variance $\left[\sigma_{\phi,\xi_t^{vol}=1} = 7.57\ (6.16, 8.97)\right]$. Despite these financial factors, in this whole period, the estimation does not provide evidence of a high interest rate response to the term

[15] Following Sims and Zha (2006) and Bianchi and Ilut (20l7), to isolate the effects of changes in the financial frictions mechanisms or monetary policy rules, we remove the credit shocks and monetary policy shocks in the respective simulations. For the counterfactuals that analyze changes in the monetary policy we remove the Taylor rule shock and keep the other sequence of shocks unaltered; while for the counterfactuals that examine the effects of the segmentation changes, we remove the credit shock and keep the other sequence of shocks changeless. For the counterfactuals that simulate the prevalence of the three volatility shocks, all the sequence of shocks remain invariable.

[16] The only exceptions are l964Ql and 1964Q4 when there is a high probability of high credit market segmentation, and l967Ql when there is a high probability of a medium credit shock variance $\left[\sigma_{\phi,\xi_t^{vol}=2} = 4.01\ (3.13, 4.90)\right]$.

*Table 8: Mean and Standard Deviation of Each Variable, in Deviations from Steady-State, Under Alternative Counterfactuals for the Analyzed Period*

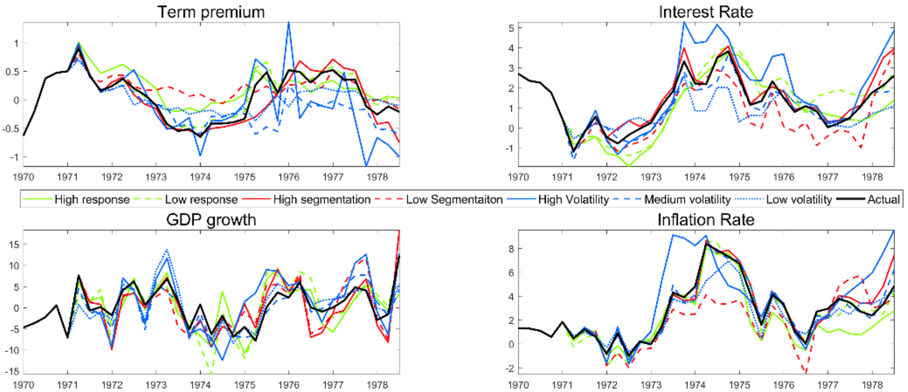
| Period | Variable | | MP | | Segmentation | | Volatilities | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | High | Low | High | Low | High | Medium | Low | Data |
| 1971q1-1978q3 | Term premium | M | 0.23 | 0.14 | 0.02 | 0.22 | -0.07 | -0.14 | 0.02 | 0.06 |
| | | SD | 0.29 | 0.40 | 0.47 | 0.20 | 0.58 | 0.34 | 0.24 | 0.41 |
| | Interest rate | M | 0.85 | 1.29 | 1.43 | 0.58 | 1.78 | 0.93 | 0.71 | 1.28 |
| | | SD | 1.52 | 1.57 | 1.37 | 1.37 | 1.99 | 1.13 | 0.73 | 1.23 |
| | GDP growth | M | 0.23 | 0.37 | 0.05 | 0.37 | 1.45 | -0.01 | 0.49 | 0.24 |
| | | SD | 5.23 | 6.39 | 6.31 | 5.97 | 6.78 | 4.71 | 5.26 | 4.56 |
| | Inflation rate | M | 2.03 | 2.60 | 3.02 | 1.86 | 3.71 | 2.86 | 2.49 | 2.65 |
| | | SD | 2.43 | 2.64 | 2.64 | 2.11 | 3.21 | 2.53 | 1.96 | 2.37 |
| 1978q4 - 1983q4 | Term premium | M | -0.14 | -0.64 | -0.29 | -0.10 | -0.40 | -0.21 | -0.13 | -0.10 |
| | | SD | 0.50 | 0.53 | 0.37 | 0.49 | 0.73 | 0.37 | 0.31 | 0.50 |
| | Interest rate | M | 6.14 | 7.91 | 7.21 | 6.04 | 9.04 | 6.72 | 5.85 | 5.75 |
| | | SD | 1.79 | 2.40 | 1.92 | 2.17 | 2.42 | 2.12 | 2.23 | 2.72 |
| | GDP growth | M | -1.10 | -2.84 | -1.76 | -1.37 | -1.21 | -1.21 | -0.73 | -0.59 |
| | | SD | 5.48 | 4.79 | 5.53 | 6.48 | 7.26 | 4.56 | 3.40 | 5.14 |
| | Inflation rate | M | 4.34 | 5.44 | 3.82 | 4.13 | 5.28 | 4.01 | 2.52 | 3.89 |
| | | SD | 1.82 | 2.41 | 2.96 | 2.75 | 1.99 | 1.65 | 2.45 | 2.32 |
| 1990q2-1993q4 | Term premium | M | 0.22 | 0.52 | -0.01 | 0.32 | 0.24 | 0.17 | 0.08 | 0.01 |
| | | SD | 0.48 | 0.76 | 0.40 | 0.60 | 0.55 | 0.43 | 0.36 | 0.64 |
| | Interest rate | M | 0.15 | -1.60 | -0.35 | 0.52 | 0.09 | 0.36 | 0.94 | 0.85 |
| | | SD | 1.67 | 2.93 | 2.17 | 1.32 | 2.02 | 1.65 | 1.33 | 2.08 |
| | GDP growth | M | -0.10 | -0.16 | -0.23 | -0.16 | -2.01 | -1.08 | -1.05 | -0.84 |
| | | SD | 2.53 | 5.26 | 3.26 | 4.42 | 4.42 | 2.51 | 3.56 | 2.11 |
| | Inflation rate | M | -0.28 | -1.16 | -1.03 | -0.23 | -1.58 | -0.02 | -0.36 | -0.08 |
| | | SD | 1.32 | 1.78 | 1.71 | 0.86 | 2.46 | 1.13 | 1.28 | 1.21 |
| 2000q4-2004q2 | Term premium | M | -0.22 | -0.17 | -0.09 | -0.10 | 0.55 | -0.14 | -0.06 | 0.24 |
| | | SD | 0.39 | 0.37 | 0.32 | 0.26 | 0.73 | 0.33 | 0.45 | 0.50 |
| | Interest rate | M | -1.93 | -2.38 | -2.20 | -1.89 | -4.84 | -1.52 | -1.50 | -1.87 |
| | | SD | 1.42 | 1.75 | 1.53 | 1.28 | 3.30 | 1.33 | 1.92 | 1.95 |
| | GDP growth | M | -1.87 | -1.64 | -1.51 | -1.23 | -1.24 | -0.76 | -0.77 | -0.27 |
| | | SD | 4.85 | 4.23 | 3.29 | 3.41 | 5.94 | 2.88 | 3.33 | 2.47 |
| | Inflation rate | M | -0.54 | -2.32 | -1.85 | -1.43 | -3.03 | -1.01 | -0.10 | -1.35 |
| | | SD | 1.62 | 1.19 | 1.48 | 1.69 | 1.96 | 0.93 | 1.39 | 0.92 |
| 2006q1-2009q4 | Term premium | M | -0.27 | -0.21 | -0.30 | -0.31 | -0.23 | -0.26 | -0.37 | -0.26 |
| | | SD | 0.40 | 0.55 | 0.62 | 0.55 | 0.75 | 0.56 | 0.41 | 0.62 |
| | Interest rate | M | -0.76 | -2.24 | -1.19 | 0.10 | -0.57 | -1.09 | -1.59 | -2.07 |
| | | SD | 1.59 | 2.03 | 2.84 | 1.27 | 1.52 | 0.78 | 0.90 | 1.71 |
| | GDP growth | M | -3.39 | -2.72 | -2.81 | -1.40 | -2.60 | -1.82 | -1.75 | -2.16 |
| | | SD | 4.23 | 4.57 | 3.50 | 2.11 | 4.47 | 1.65 | 2.60 | 3.28 |
| | Inflation rate | M | -1.18 | -0.73 | -0.99 | -0.33 | -1.44 | -1.14 | -1.22 | -1.14 |
| | | SD | 1.66 | 2.86 | 2.28 | 1.80 | 4.02 | 1.38 | 1.26 | 2.40 |
| 2010q1-2011q4 | Term premium | M | 0.40 | 0.88 | 0.49 | 0.40 | 0.42 | 0.52 | 0.43 | 0.55 |
| | | SD | 0.39 | 0.30 | 0.31 | 0.19 | 0.65 | 0.34 | 0.35 | 0.33 |
| | Interest rate | M | -5.53 | -5.70 | -5.16 | -5.03 | -5.73 | -4.99 | -4.93 | -4.98 |
| | | SD | 0.74 | 0.40 | 0.25 | 0.58 | 0.45 | 0.11 | 0.11 | 0.23 |
| | GDP growth | M | -0.97 | -1.49 | -0.38 | 0.69 | -1.34 | -1.29 | -0.08 | -2.70 |
| | | SD | 2.99 | 2.63 | 2.23 | 1.26 | 3.00 | 1.85 | 1.91 | 3.72 |
| | Inflation rate | M | -2.31 | -3.34 | -2.11 | -2.05 | -0.97 | -1.33 | -1.32 | -2.21 |
| | | SD | 0.98 | 1.42 | 1.04 | 1.03 | 1.76 | 0.90 | 0.76 | 2.55 |

premium even when the Federal Reserve raised rates in 1971Q3 and 1972Q1 to fight inflation. It is important to keep in mind that during this period, Richard Nixon unilaterally cancelled the international convertibility of the US dollar to gold in 1971Q3; the world economy faced the 1973Q3 oil shock due to the Organization of the Petroleum Exporting Countries' embargo; and the US government ran deficits to pay for the Vietnam war and President Lyndon Johnson's Great Society Programs. Also, according to the NBER's Committee, there was an economic contraction from 1973Q4 to 1975Q1.

Figure 14 shows the first counterfactual exercise focused on this episode when as mentioned there is a high probability of regime switches related to financial frictions and shocks volatility. In 1971Q1, the term premium was above its steady-state level, interest rates dropped from 8.98% in December 1970 to 3.72% in February 1971, GDP growth was below steady state and inflation was low but above steady state. Comparing the effects of financial frictions, the red solid line of high credit market segmentation partially explains why the term premium dropped sharply, inflation rose, the interest rates increased, and output growth was smaller, relative to the red dashed line of low credit market segmentation where the term premium would have stayed closer to steady state, there would have been a more moderate increase in inflation, interest rates would have increased less, and output growth would have been bigger than the data. Obviously, there were other important domestic and external factors affecting the economy, but these factors would have been present regardless of the level of financial frictions. The opening quote in the paper by Bernanke talks about the dangerous effects of persistent deviations of the term premium from its steady state, here we see that high credit market segmentation caused these deviations to be larger and more persistent. What could have happened if the monetary authority had responded more aggressively to the term premium (solid green versus dashed green lines)? Interest rates would have remained lower during the whole episode, and although inflation would have been slightly higher until 1973Q2, for the remaining of the sample (1973Q3-1978Q3) it would have been on average 1% lower than with a 100% probability of high response and 1.2% lower than the data. The trade-off to this important inflation reduction is that output growth would have been lower by 0.5%. If shocks volatility had been lower (dotted blue), inflation and interest rates would have been lower and less volatile, while average output growth would have been higher than the data.

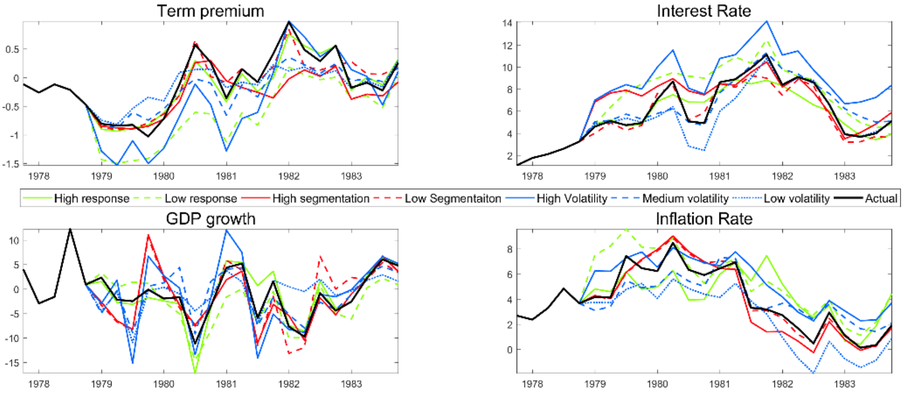
Figure 15 shows the first time when our estimation assigns a high probability to a high interest rate response to the term premium $\left[\tau_{tp,\xi_t^{mp}=1} = -1.16\ (-1.20, -1.10)\right]$ from 1978Q4 to 1983Q4. In this episode the estimation assigns a high probability to high credit market segmentation in 1980Q1 and 1980Q2, 1982Q3 and 1982Q4, and 1983Q4. Meanwhile, the estimation assigns a high probability of a high credit shock volatility from 1981Q3 to 1984Q4. With inflation and interest rates rising during the late 1970s and early 1980s, savings and loan institutions that had regulation on maximum interest rates that they could pay to depositors saw their funding base eroded, while the fixed-rate interest that they earned in their mort- gages represented large valuation losses in their assets. Despite the Depository Institutions Deregulation and Monetary Control Act of 1980, which prompted industry deregulation, it turned out insufficient eventually requiring taxpayer's bailout.

*Figure 14: Counterfactual simulation from 1971Q1 to 1978Q3*




*Note: For the counterfactuals, the solid green lines show the simulated series for the high response to term premium scenario, while the green dashed lines display the simulated series for the low response to term premium scenario. The solid red lines show the simulated series for the high segmentation scenario, while the dashed red lines display the low segmentation scenario. The solid blue lines report the simulated series for the high volatility scenario, while the dashed blue lines and the dotted blue lines report the simulated series for the medium volatility and low volatility scenarios, respectively. The solid black line shows the observed series.*

*Figure 15: Counterfactual simulation from 1978Q4 to 1983Q4*



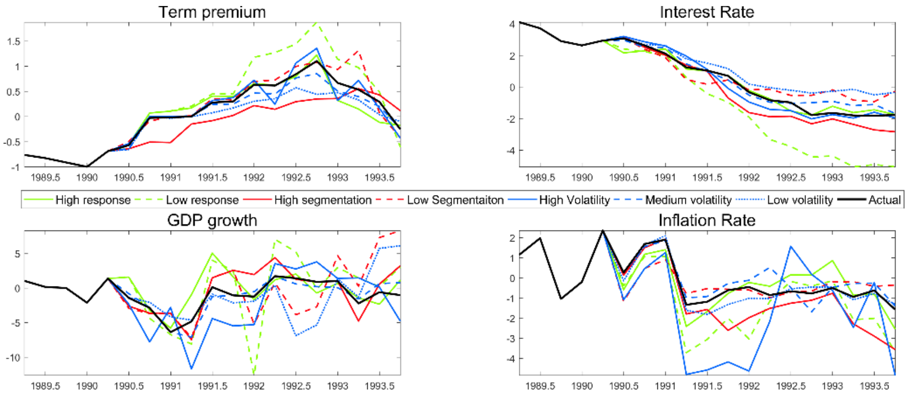

*Note: For the counterfactuals, the solid green lines show the simulated series for the high response to term premium scenario, while the green dashed lines display the simulated series for the low response to term premium scenario. The solid red lines show the simulated series for the high segmentation scenario, while the dashed red lines display the low segmentation scenario. The solid blue lines report the simulated series for the high volatility scenario, while the dashed blue lines and the dotted blue lines report the simulated series for the medium volatility and low volatility scenarios, respectively. The solid black line shows the observed series.*

The high interest rate response to term premium, which according to the estimation started three quarters before Paul Volcker were appointed as Federal Reserve's chairman, came when the term premium was below steady state, inflation was relatively high and rising, interest rates were also rising, and GDP was above trend. In 1979Q4 there was a negative oil supply shock related to the Iraq and Iran war. The NBER's Committee identifies two recessions in this episode, from 1980Q1 to 1980Q3 and from 1981Q3 to 1982Q4.

What if the interest rate response had not changed (dashed green line) relative to a fully credible regime switch in monetary policy (solid green line)? With a low response interest rate, the term premium would have been much lower deviating from the steady state until 1982Q1, GDP would have expanded, but at the cost of much higher inflation, which eventually would have required higher interest rates. Meanwhile, if credit shock volatility would have been lower (dotted blue), the term premium would have been closer to the steady-state level, with lower inflation and interest rates without excessive GDP fluctuations.

Figure 16 displays the counterfactual exercise for our next analyzed episode is 1990Q2 to 1993Q4 when interest rate response to the term premium is also estimated high with high probability. Starting in 1990Q3, the Federal Open Market Committee lowered interest rates from 8.25% to 4% by the end of 1991 and to 3% by 1992Q3. Meanwhile, the NBER's Committee dates a contraction from 1990Q3 to 1991Q1.

*Figure 16: Counterfactual simulation from 1990Q2 to 1993Q4*




*Note: For the counterfactuals, the solid green lines show the simulated series for the high response to term premium scenario, while the green dashed lines display the simulated series for the low response to term premium scenario. The solid red lines show the simulated series for the high segmentation scenario, while the dashed red lines display the low segmentation scenario. The solid blue lines report the simulated series for the high volatility scenario, while the dashed blue lines and the dotted blue lines report the simulated series for the medium volatility and low volatility scenarios, respectively. The solid black line shows the observed series.*

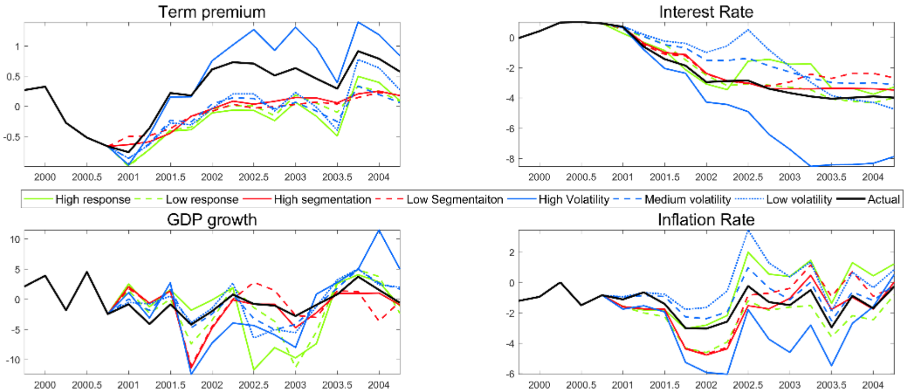
The estimation assigns a high probability to high financial frictions from 1990Q2 to 1991Q2 and on 1993Q1 and 1993Q2, while credit shock volatility has a high probability of being of medium magnitude in 1990Q4 and from 1993Q1 to 1993Q3. The Federal Deposits and Insurance Corporation (FDIC) experienced an improvement after President George H. W. Bush responded to the problems in the banking and thrift industries which have their origins two decades before. By the end of 1991, nearly 1,300 commercial banks either failed or required failing assistance from the FDIC causing its severe undercapitalization. The main overarching provisions of the FDIC Improvement Act, which was implemented in 1994, include *prompt corrective action* and *least cost resolution*. This process was followed by the Riegle-Neal Act of September 1994 that allowed banks to branch at intra-and interstate levels.

In this episode, term premium was below the steady state but rose quickly. A low response to term premium (green dashed) would have implied a sharper cut in interest rates and a longer and deeper recession, while a fully-credible high response policy (green solid) would have cut interest rates less, but earlier, and could have shortened and mitigated the recession. According to the low response policy, term premium would have spiked, and there could have been a huge economic contraction in 1992Q1. Regarding financial frictions, it calls the attention that with higher credit market segmentation (solid red) the term premium would have raised less, interest rates would have fallen more since 1990Q3 and the GDP growth recovery would have been strong until 1993Q1 when the observed high financial frictions dragged GDP growth. Low shocks volatility (blue dot- ted) would have implied a lower term premium, and the recession would have been smaller despite less aggressive interest rate cuts, while high volatility (blue solid) would cause higher term premium and a much deeper recession.

Figure 17 shows the counterfactual exercise for our next analyzed episode is 2000Q4 to 2004Q2 when there is a high probability of medium credit shock volatility from 2000Q4 to 2001Q3 and from 2003Q3 to 2004Q2, and of high financial frictions in 2001Q4 and from 2002Q3 to 2003Q3. It is important to mention that in 1999Q4 President Bill Clinton signed into law the Financial Services Modernization Act, commonly called Gramm-Leach-Bliley Act. This law repealed the Glass-Steagall Act and gave the Federal Reserve new supervisory powers. With this legislation, it was intended to promote the benefits of financial integration for consumers and investors, while safeguarding the soundness of the banking and financial systems. Now commercial and investment banking, separated since 1933, would not have restrictions of integration between them leading to the creation of the financial holding groups (Mahon, 2013). The most common case is the merger and acquisition of Travelers Group with Citicorp, forming the nowadays well-known Citigroup. In this period the Federal Reserve also played an active role as a supervisor of the financial holding companies (FHC). The Federal Reserve supervises the consolidated organization, while primarily relying on the reports and supervision of the appropriate state and federal authorities for the FHC subsidiaries, taking the role of an *umbrella* supervisor. This necessity surge because these large FHC had risk spread across their subsidiaries but managed it as a consolidated entity.

In this episode there is a low probability of a high monetary pol- icy response to the term premium. The NBER's Committee dates a contraction from 2001Q1 to 2001Q4 and starting in January 2001; the Federal Open Market Committee cut interest rates 11 times that year from 6.5% to 1.75%. Comparing the green lines, we see that with a more responsive monetary policy rate, that had lowered interest rates more steeply, would have resulted in a lower term premium and it might have delayed an output contraction until 2002Q3, but the contraction might have ended being more severe, while inflation would have been larger. The red dashed line provides evidence that if high financial frictions had not been present the economy would have experienced a stronger recovery since 2002Q3. The sol- id blue line shows that if shocks had been high, the economy would have suffered a much more volatile cycle with higher term premium, much lower interest rates, greater output contraction, and even a prolonged deflation.

*Figure 17: Counterfactual simulation from 2000Q4 to 2004Q2*



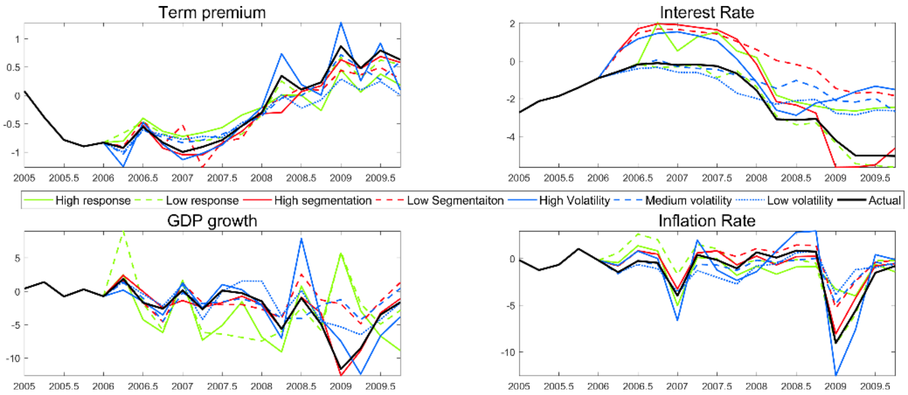

*Note: For the counterfactuals, the solid green lines show the simulated series for the high response to term premium scenario, while the green dashed lines display the simulated series for the low response to term premium scenario. The solid red lines show the simulated series for the high segmentation scenario, while the dashed red lines display the low segmentation scenario. The solid blue lines report the simulated series for the high volatility scenario, while the dashed blue lines and the dotted blue lines report the simulated series for the medium volatility and low volatility scenarios, respectively. The solid black line shows the observed series.*

Figure 18 displays the counterfactual exercise for our next analyzed episode is 2006Q1 to 2009Q4 when there is a high probability of medium credit shock volatility in 2006Q3, 2008Q2, and 2008Q3, and high volatility in 2008Q4, while high frictions are identified in 2006Q1-2008Q1 and 2009Q2-2010Q1. Despite being the episode directly related with our opening quote, where recently appoint- ed Chairman Bernanke was highlighting the risks of financially stimulative declines in the term premium and the need of greater monetary policy restraint, in this episode there is a low probability of a high monetary policy response to the term premium.

This episode is preceded by a Federal Reserve's funds target that in June 30, 2004, started an upward trend from the 1% prevailing since June 25, 2003, to 2.25% by the end of 2004, and 4.25% by the end of 2005. During the first half of the year the Federal Open Market Committee added other four 0.25% increments to 5.25% by June 2006. What could have happened if monetary policy was more responsive towards the term premium? According to the counterfactual, the solid green line shows that this would have implied rising interest rates by an additional 2%, which would have significantly slowed down economic activity. However, GDP growth did not have the large boom-bust cycle implied by a 100% probability of low monetary policy response as depicted by the dashed green line.

The comparison of the red solid line of high financial frictions and red dashed line of low financial frictions allows us to see the important role that credit market imperfections played in the 2007Q4 to 2009Q2 output contraction. The presence of high financial frictions also allows us to understand why the Federal Reserve need- ed to be so aggressive lowering interest rates during the recession lowering them to 4.25% by the end of 2007 and to [0%-0.25%] on December 16, 2008. Meanwhile, the comparison of the three blue lines related to the magnitude of shocks volatility shows that if this had remained high in 2009Q1 and 2009Q2, the output contraction would have deepened.

*Figure 18: Counterfactual simulation from 2006Q1 to 2009Q4*




*Note: For the counterfactuals, the solid green lines show the simulated series for the high response to term premium scenario, while the green dashed lines display the simulated series for the low response to term premium scenario. The solid red lines show the simulated series for the high segmentation scenario, while the dashed red lines display the low segmentation scenario. The solid blue lines report the simulated series for the high volatility scenario, while the dashed blue lines and the dotted blue lines report the simulated series for the medium volatility and low volatility scenarios, respectively. The solid black line shows the observed series.*

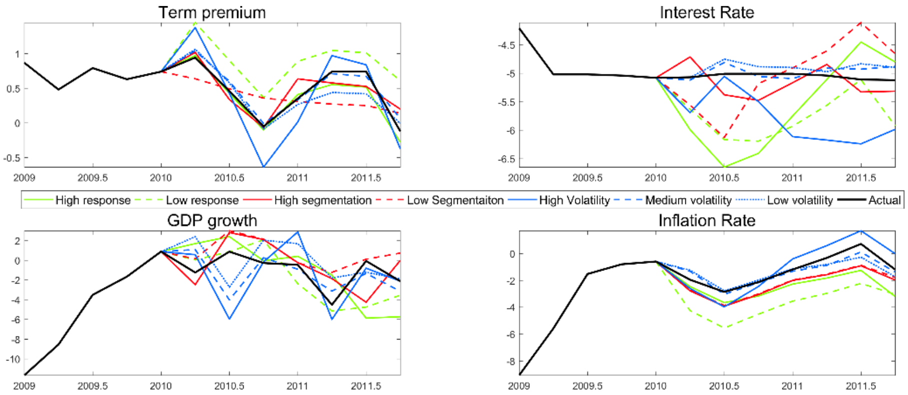
This period includes the most critical events of the subprime crisis. According to Calomiris and Haber (2014), there is no consensus among scholars, practitioners, and politicians about the key causes of the subprime crisis. Some theories explaining this crisis include the creation of new and riskier financial securities like the mortgage back securities and other financial derivatives; the excessive risk taking by government-sponsored enterprises such as Fannie Mae and Freddie Mac; and the Bush-era free market ideology. Pushing Fannie and Freddie to purchase highly leveraged risky mortgages to in- crease the liquidity and the capability of the lenders to extend more credits targeted to specific borrowers had huge effects on the mort- gage markets. The mortgage securities market was highly unregulated. Financial indicators such as the LIBOR/OIS spread gave signs of stress and uncertainty in the US economy. Rating agencies played a big role in this event. Credit ratings assigned by rating agencies affected the allocation of risk capital in the economy. Higher credit ratings allowed firms to borrow at better terms and thus positively affect a firm's value (Bae et al., 2015). After the market crash, the Federal government of the US and the Federal Reserve took unprecedented actions. Fannie Mae and Freddie Mac became government owned banks after their bailout. Liquidity-support programs were designed to support the different markets in distress (Calomiris and Haber, 2014). As a measure of prevention and supervision, President Obama passed the Dodd-Frank Act to reform and regulate the banking system through the creation of a series of governmental agencies.

Figure 19 shows the counterfactual exercise for our last analyzed episode is 2010Q1 to 2011Q4 when there is a high probability of a high interest rate response to the term premium. Financial frictions are estimated to be high in 2010Q4 and 2011Q4, while medium credit shock volatility has a high probability of having taken place in 2010Q2 and from 2011Q2 to 2011Q4. It is important to have in mind that the Federal Reserve funds rate was in a zero-lower bound from December 2008 to December 2015. The economy was recovering from a recession, and the term premium was above the steady state. The behavior of the term premium is followed closely by the one of high monetary policy response, high financial frictions, and medium and low shocks volatility. The high interest rate response would have implied lowering interest rates by an additional 1.5% in 2010Q4, which compares to an average −0.95% in 2010Q4 and −1.23% in 2011 according to the quantitative easing adjusted shadow interest rate in Wu and Xia (2015). If financial frictions had been low during the entire episode GDP growth could have always been above the observed level, while if responsive monetary policy had been fully credible GDP growth would have been also higher until 2011Q2.

In the aftermath of the 2007-2009 crisis, President Barack Obama noticed that "the financial sector was governed by antiquated and poorly enforced rules that allowed some to take risks that endangered the economy." The US Congress, the White House, and the Federal Reserve took actions to improve the actual regulation of the financial sector. By the last quarters of 2009, these authorities began their participation in the craft of the Dodd-Frank Wall Street Reform and Consumer Protection Act.

In 2010Q1, the Federal Reserve announced QE2, buying USD 600 billion in longer-term Treasury securities. By this time, Bernanke began his second term as Federal Reserve chairman. Also, the Dodd- Frank financial reform became law, and the Federal Reserve issued guidelines for evaluating large bank holding companies' capital action proposals. By 2011, the Consumer Financial Protection Bureau opened its doors, procuring the health and protection of the consumers by supervising disclosure of banks, lenders, and other financial companies. Around the globe, Greece admitted a deficit-to-GDP ratio of 12% (2009Q4) so that the International Monetary Fund and the European Central Bank ran the first rescue plan and completed it two quarters later. By the third quarter of 2011 the Financial Stability Board cleared to purchase sovereign bonds.

*Figure 19: Counterfactual simulation from 2010Q1 to 2011Q4*




*Note: For the counterfactuals, the solid green lines show the simulated series for the high response to term premium scenario, while the green dashed lines display the simulated series for the low response to term premium scenario. The solid red lines show the simulated series for the high segmentation scenario, while the dashed red lines display the low segmentation scenario. The solid blue lines report the simulated series for the high volatility scenario, while the dashed blue lines and the dotted blue lines report the simulated series for the medium volatility and low volatility scenarios, respectively. The solid black line shows the observed series.*

## 7. CONCLUSIONS

This paper shows the importance of considering Markov-switching when analyzing macroeconomic-financial nexus either in VAR and DSGE models. Evidence comes from the comparison of estimated constant coefficients and constant variance VAR and of different specifications of varying coefficients and/or varying variance MS-VAR models. To provide an economic interpretation to those coefficients and variance, we augment with Markov-switching a DSGE macroeconomic model with financial frictions in long-term debt instruments developed by Carlstrom, Fuerst and Paustian (2017) and compare the estimations of time-invariant parameters and shocks DSGE versus various specifications of MS-DSGE models.

Based on a model fit criterion, the introduction of Markov switching in parameters and variances improves the fit of a macroeconomic VAR model with financial variables, with the best fit in an unrestricted model with two switches in coefficients and three switches in variances (2*c*3*v*). The introduction of Markov switching in parameters and especially in variances, also greatly improves the fit of a DSGE macroeconomic model, with the best fit in a model with 2 regimes in financial market segmentation, 2 regimes in the monetary policy interest rate response to the term premium, and 3 regimes in the credit shock volatilities (2S2R3V).

In the used DSGE model, when allowing for switching in the parameters capturing financial frictions and monetary policy and switching in shocks volatilities there are different, well defined, regimes of high and low financial frictions, high and low monetary policy response to the term premium and high (, medium) and low credit shock volatilities regimes.

To fit the data, an estimated time-invariant DSGE produces larger shocks relative to a DSGE model with Markov-switching in parameters. An estimated DSGE without Markov-switching in parameters misinterprets structural regime switches as large shocks events. Meanwhile, an estimated DSGE without Markov-switching in shocks overestimates the high coefficients regimes. The IRFs are markedly different depending on the regime the economy is under.

The Bayesian maximum likelihood estimation of the 2S2R3V MS-DSGE model, which is the one with the best fit to the data, identifies 59 quarters (27% of the sample that runs from 1962Q1 to 2017Q4) when financial frictions, measured by the financial intermediaries' portfolio adjustment costs to their net worth, had a large probability of being high, with the following relevant intervals: 1971Q1-1971Q4, 1976Q3-1978Q3, 1983Q4-1985Q4, 1990Q2-1991Q2, 2002Q3-2003Q3, 2006Q1-2008Q1, and 2009Q2-2010Q1.

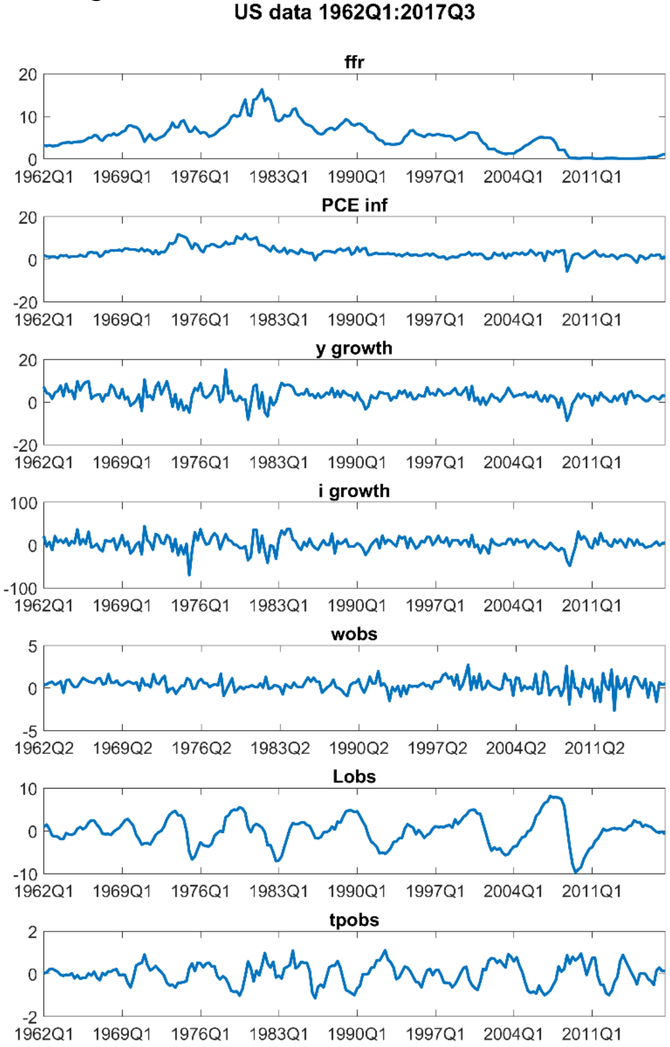
Also, there are 43 quarters (19.3%) when the interest rate response to the term premium is estimated high, with the following intervals: 1978Q4-1983Q4, 1990Q2-1993Q4, and 2010Q1-2011Q4. In addition, the MS-DSGE estimation has 34 quarters (15.2%) of large probability of high credit shock volatility, 46 quarters (20.6%) with a large probability of medium credit shock volatility and 142 quarters (63.7%) with a large probability of low credit shock volatility.

We analyzed six episodes when financial frictions were high and/or credit shocks volatility was either medium or high denoting disruptions in financial markets. In three of those episodes, 1978Q4-1983Q4, 1990Q2-1993Q4, and 2010Q1-2011Q4, short-term interest rates had a high response to the term premium. In the other three periods of financial distress, 1971Q1-1978Q3, 2000Q4-2004Q4, and 2006Q1-2009Q4, short-term interest rates had a low response. Counterfactual exercises allowed us to analyze what could have happened under alternative credit market conditions and monetary policy responses. These counterfactuals provide evidence of the amplifying effects of financial factors and the role that monetary policy has had mitigating financially driven business cycles.

# ANNEXES

## *Annex 1. Data*

*Figure A1: Data used in the estimations*

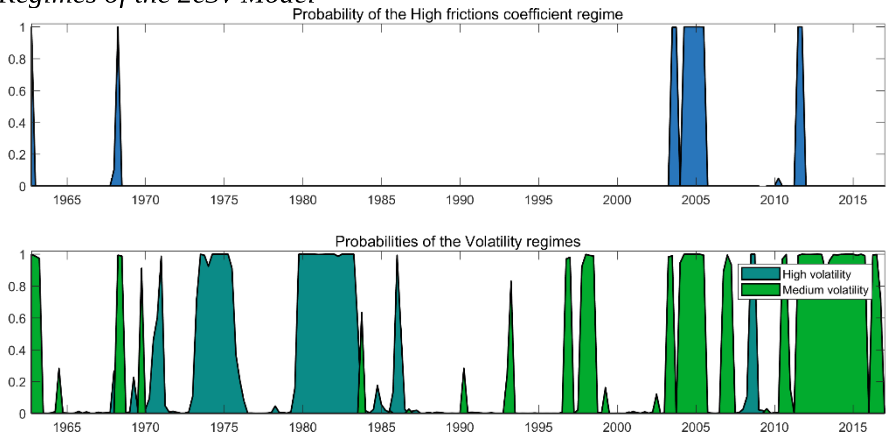



*Note. We use US data from 1962Q1 to 2017Q3 for the estimation of the model. The database takes the original series reported in Carlstrom et al. (2017) but extend the sample from 2008Q4 to 2017Q3. Quarterly series were selected for the annualized growth rates of real GDP, real gross private domestic investment, real wages, inflation rate–personal consumption expenditure index– and real wages. The labor input series was constructed substituting the trend component from the nonfarm business sector (hours of all persons) series. The series for the federal funds rate is obtained averaging monthly figures downloaded from the Federal Reserve Bank of St. Louis's website. Additionally, for the term premium, we take the Treasury term premia series from the Federal Reserve Bank of New York's website, estimated by Adrian et al. (2013). All data are demeaned.*

### *Annex 2. Probabilities of Switching Coefficients and Variance States of the MS-VAR Model with Best Fit 2c3v*

Figure A2 reports the probabilities of switching coefficients of the high stress coefficient and the high and medium stress variance for the 2*c*3*v* MS-VAR model, which is the one with the best fit to the data. The MS-VAR estimation identifies 12 quarters (5.5% of the MS-VAR sample that runs from 1962Q4 to 2017Q1) with a large probability of being in a high-stress coefficient state and the remaining 206 quarters (94.5%) of a low-stress coefficient state[17]. Meanwhile, regarding variance switching the estimation identifies 32 quarters (14.7%) of high probability of being in a high-stress variance state, 49 quarters (22.5%) of medium-stress variance state and 137 quarters (62.8%) of low-stress variance state. The historical narrative of the regime switching in coefficients and variances is provided in section 6.4 when we analyze the regime switches of the DSGE models.

*Figure A2: Smoothed Probabilities of MS-VAR Coefficients and Variances Regimes of the 2c3v Model*



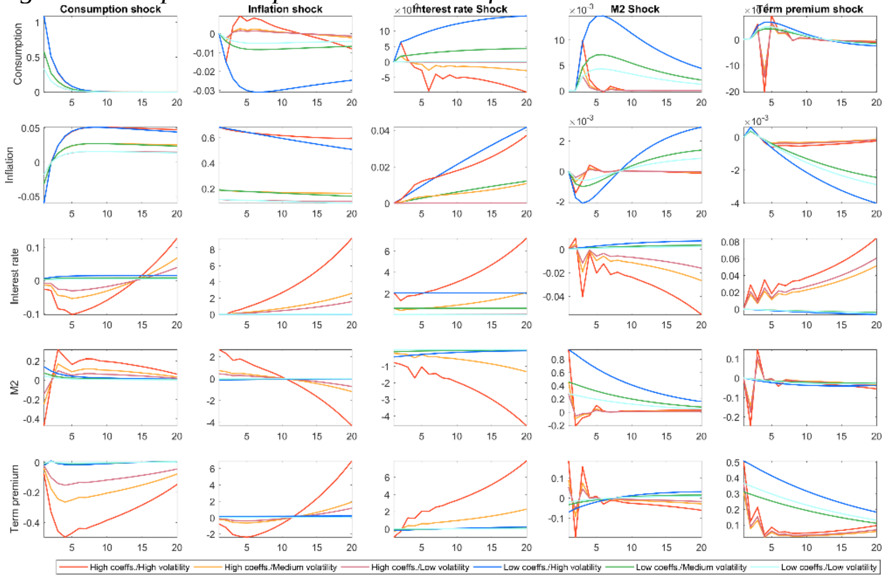

*Note: The top panel reports the probability of high frictions coefficient regime. The second panel reports the probability of high and medium volatility regimes.*

[17] The results for the 2*c*3*v* model do not show many switches in the probabilities of the coefficients. However, if we restrict the model to other specifications in the interest rate, money supply and term premium equations, such as 2*c*RM3*v*, 2*c*TPR3*v* and 2*c*TPRM3*v* the smoothed probabilities for the coefficients have more fluctuation. These models report frictions for the coefficient in the following percentages of the sample: 18%, 32%, and 32%, respectively. As we show in section in section 6.3, these results are more consistent with the MS-DSGE specification results, where high financial frictions are present in 26.5% of the sample, while high monetary policy response is present in 19.3%.

### *Annex 3. MS-VAR Impulse Response Functions of the Model with Best Fit 2c3v*

Figure A3 reports the impulse response functions for the 2c3v MS-VAR model, which is the one with the best fit to the data. There we see that the varying coefficients and the varying volatilities generate different responses for any given variable. The important differences in magnitude and persistence for the high (reds) versus low (blues) coefficient regimes, which yields a distorting scale in some responses, are notable. Also, there are significant differences in the responses when comparing the high (darker color), medium and low variance regimes. For example, for a term premium shock, a high coefficient regime has a transitory effect on term premiums, a sharp drop in consumption growth and raising interest rates, which contrast with the low coefficient regime where the effect on term premium lasts longer, and there is no contraction in consumption growth, neither change in interest rates. Another example is the behavior of the variables to an interest rate shock, where under the high coefficient regime, the term premium raises sharply, and consumption growth declines, with the exception when the high coefficient regime intersects with the low variance regime (which only occurred in 2003Q4) where some of the dynamics are closer to the low coefficient regime.

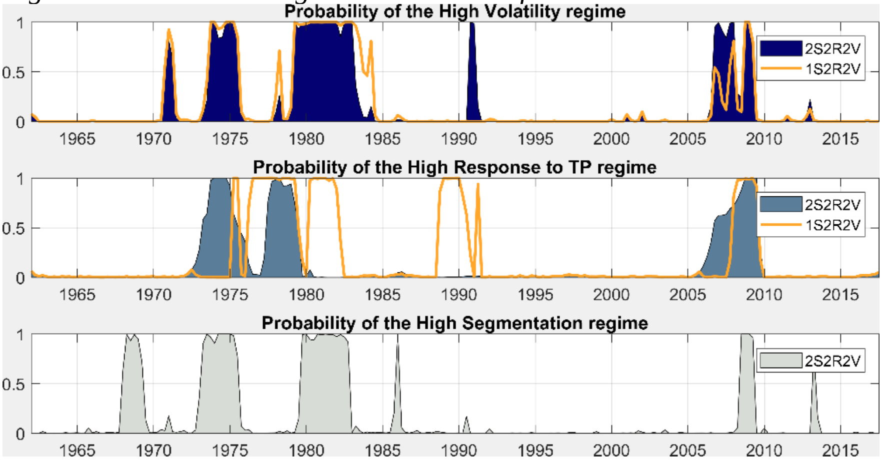
*Figure A3: Impulse Response Functions of the 2c3v MS-VAR*




*Note: High coefficient regimes are presented in red-like colors, while low coefficient regimes are shown in blue-like colors. The darker the color of the line, the greater the variance volatility regime.*

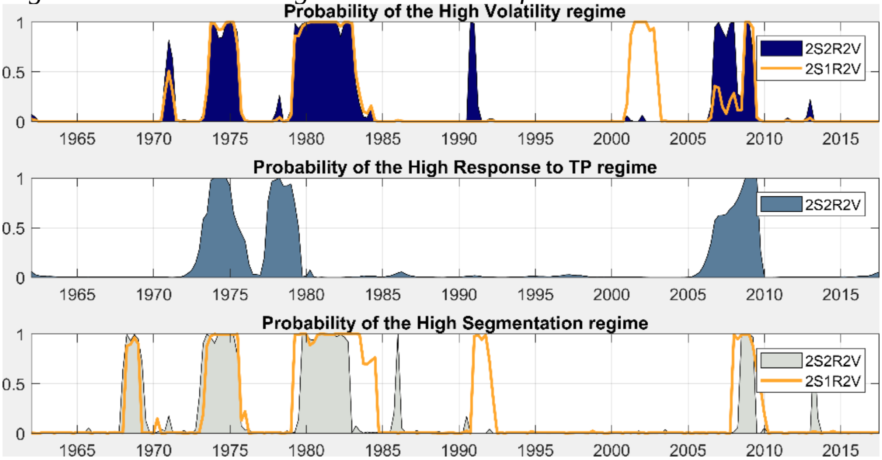
*Annex 4. Comparison of the Estimated Regime Probabilities of the MS-DSGE Models at the Posterior Mode*

*Figure A4: Estimated Regime Probabilities for 2S2R2V vs. 1S2R2V*



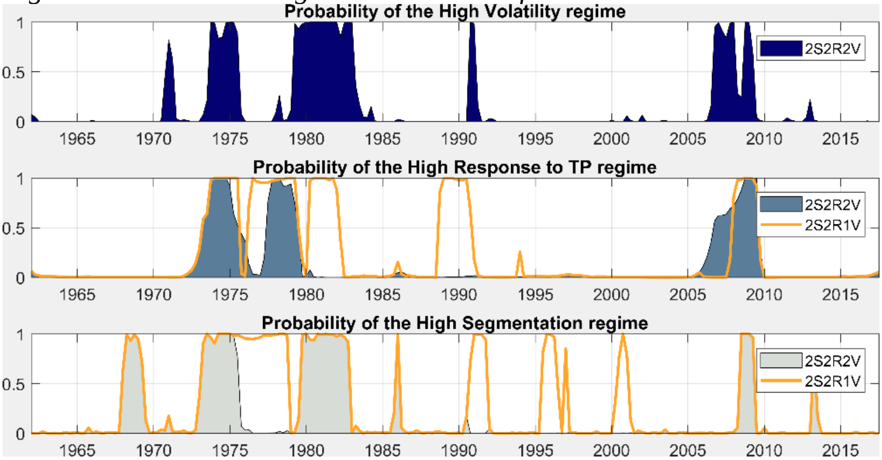

*Note: The top panel depicts the probability of the high volatility regime; the medium panel, the probability of the high response to term premium regime; and the bottom panel, the probability of the high segmentation regime.*

*Figure A5: Estimated Regime Probabilities for 2S2R2V vs. 2S1R2V*



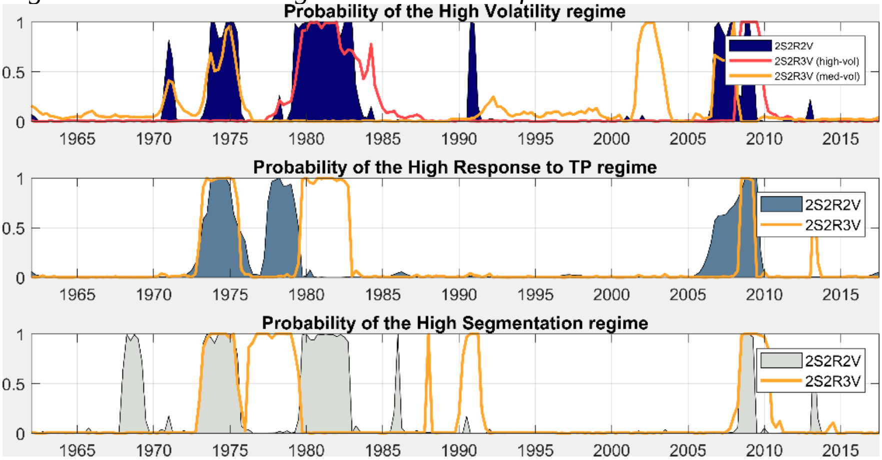

*Note: The top panel depicts the probability of the high volatility regime; the medium panel, the probability of the high response to term premium regime; and the bottom panel, the probability of the high segmentation regime.*

*Figure A6: Estimated Regime Probabilities for 2S2R2V vs. 2S2R1V*



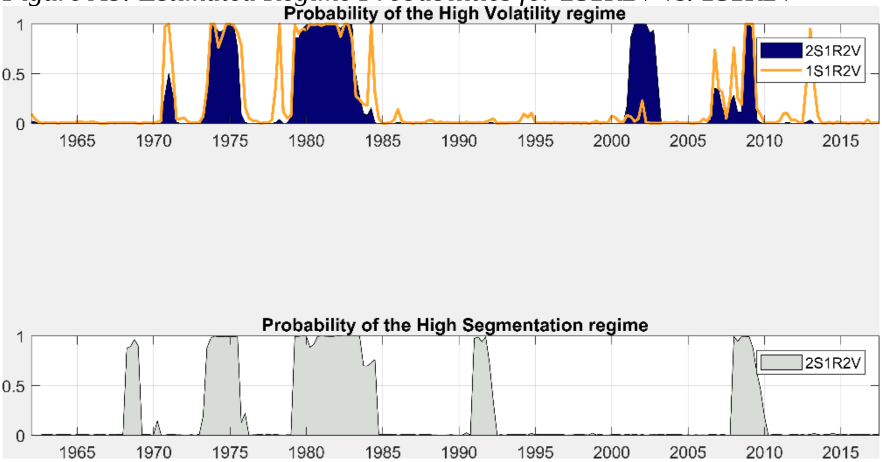

*Note: The top panel depicts the probability of the high volatility regime; the medium panel, the probability of the high response to term premium regime; and the bottom panel, the probability of the high segmentation regime.*

*Figure A7: Estimated Regime Probabilities for 2S2R2V vs. 2S2R3V*



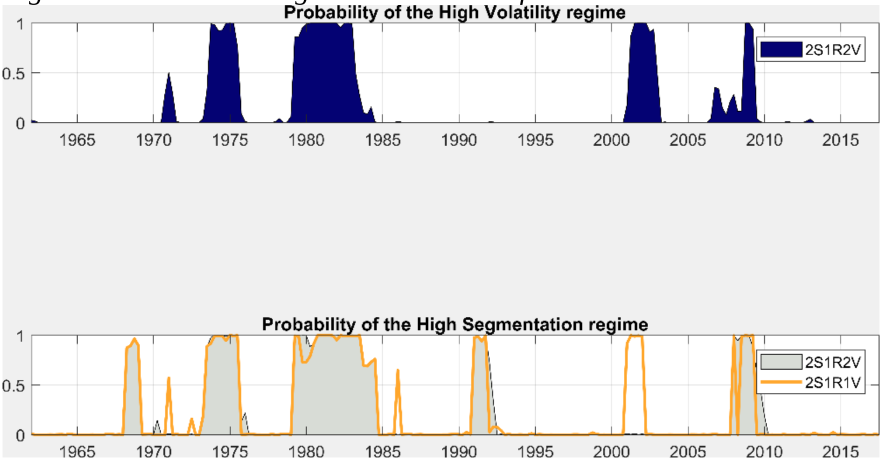

*Note: The top panel depicts the probabilities of the high and medium volatility regime; the medium panel, the probability of the high response to term premium regime; and the bottom panel, the probability of the high segmentation regime.*

*Figure A8: Estimated Regime Probabilities for 2S1R2V vs. 1S1R2V*



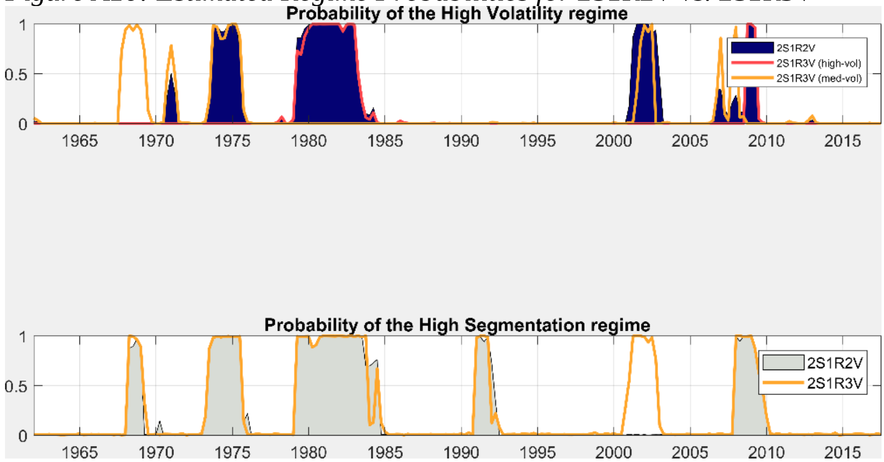

*Note: The top panel depicts the probability of the high volatility regime; and the bottom panel, the probability of the high segmentation regime. There is no middle panel as both models restrict switching in the response to term premium.*

*Figure A9: Estimated Regime Probabilities for 2S1R2V vs. 2S1R1V*




*Note: The top panel depicts the probability of the high volatility regime; and the bottom panel, the probability of the high segmentation regime. There is no middle panel as both models restrict switching in the response to term premium.*

*Figure A10: Estimated Regime Probabilities for 2S1R2V vs. 2S1R3V*

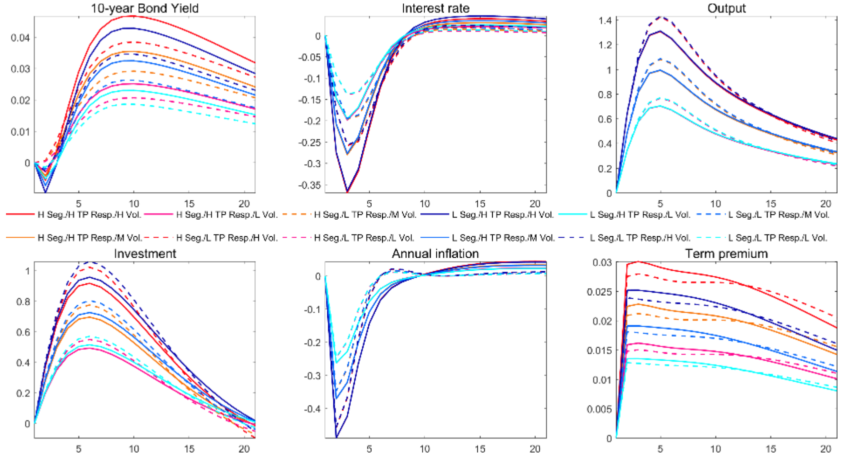



*Note: The top panel depicts the probabilities of the high and medium volatility regime; and the bottom panel, the probability of the high segmentation regime. There is no middle panel as both models restrict switching in the response to term premium.*

### *Annex 5. Impulse Response Functions of the 2S2R3V MS-DSGE Model*

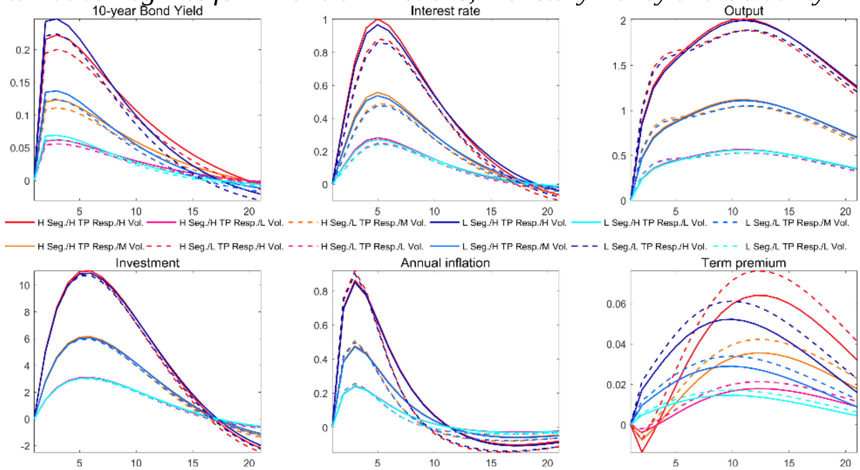
This annex shows the impulse responses to a one-standard deviation shock to neutral technology, $\sigma_a$, investment-specific, $\sigma_\mu$, price markup, $\sigma_{mk}$, wage markup, $\sigma_w$, and intertemporal preference, $\sigma_{rn}$. As described in the text, each figure has 12 lines which depict the responses under the two alternative financial friction (H Seg. and L Seg.), the two monetary policy responses to term premium (H T P Resp. and L T P Resp.), and the three credit shock volatilities (H. Vol., M Vol. and L Vol.) regimes. High financial frictions regimes are presented in red-like colors, while low ones are presented in blue-like colors. High monetary policy response regimes are presented in solid lines, while low ones are presented in dashed lines. High volatility regimes have the darkest colors, medium mild tones, and low ones are in the lightest tones.

*Figure A11. Impulse Response Functions of the 2S2R3V MS-DSGE Model to a One Standard Deviation Neutral Technology Shock Under Alternative Regimes for Financial Frictions, Monetary Policy and Volatility*



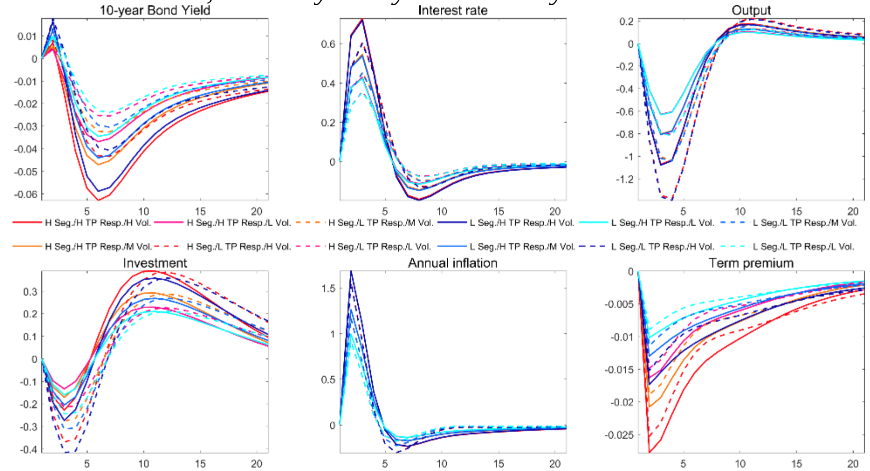

*Note: High financial frictions regimes are presented in red-like colors, while low ones are presented in blue-like colors. High monetary policy response regimes are presented in solid lines, while low ones are presented in dashed lines. High volatility regimes have the darkest colors, medium mild tones, and low ones are in the lightest tones.*

*Figure A12. Impulse Response Functions of the 2S2R3V MS-DSGE Model to a One Standard Deviation Investment-Specific Technology Shock Under Alternative Regimes for Financial Frictions, Monetary Policy and Volatility*



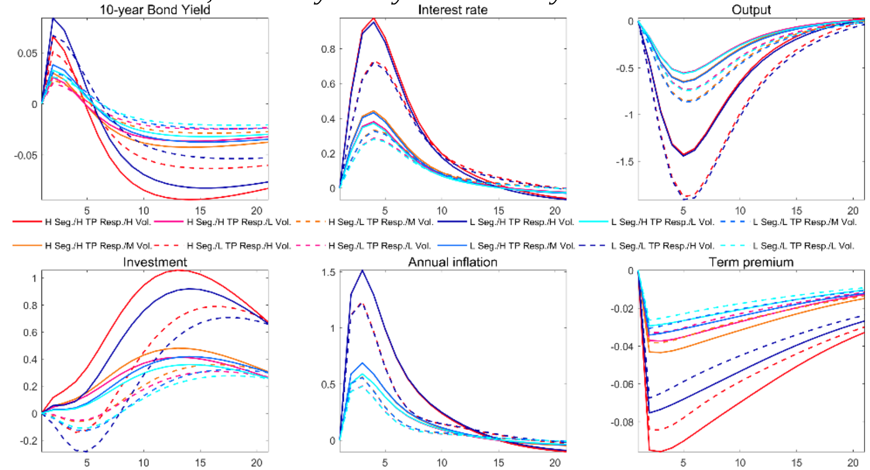

*Note: High financial frictions regimes are presented in red-like colors, while low ones are presented in blue-like colors. High monetary policy response regimes are presented in solid lines, while low ones are presented in dashed lines. High volatility regimes have the darkest colors, medium mild tones, and low ones are in the lightest tones.*

*Figure A13. Impulse Response Functions of the 2S2R3V MS-DSGE Model to a One Standard Deviation Price Markup Shock Under Alternative Regimes for Financial Frictions, Monetary Policy and Volatility*



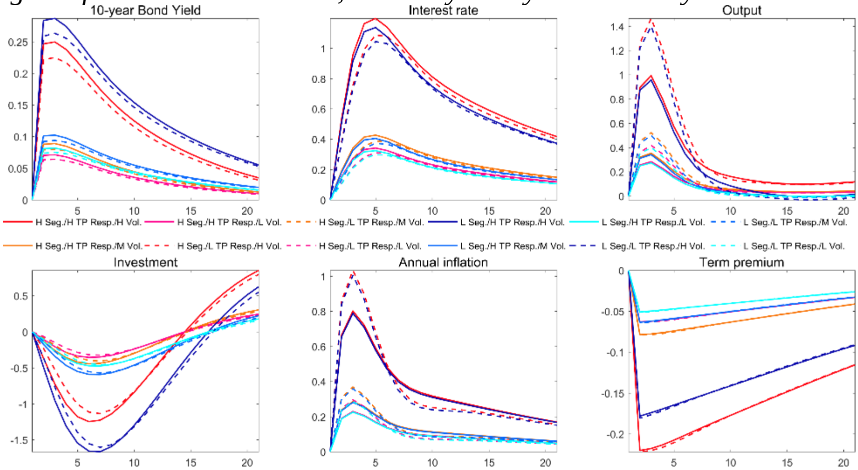

*Note: High financial frictions regimes are presented in red-like colors, while low ones are presented in blue-like colors. High monetary policy response regimes are presented in solid lines, while low ones are presented in dashed lines. High volatility regimes have the darkest colors, medium mild tones, and low ones are in the lightest tones.*

*Figure A14. Impulse Response Functions of the 2S2R3V MS-DSGE Model to a One Standard Deviation Wage Markup Shock Under Alternative Regimes for Financial Frictions, Monetary Policy and Volatility*




*Note: High financial frictions regimes are presented in red-like colors, while low ones are presented in blue-like colors. High monetary policy response regimes are presented in solid lines, while low ones are presented in dashed lines. High volatility regimes have the darkest colors, medium mild tones, and low ones are in the lightest tones.*

*Figure A15. Impulse Response Functions of the 2S2R3V MS-DSGE Model to a One Standard Deviation Intertemporal Preference Shock Under Alternative Regimes for Financial Frictions, Monetary Policy and Volatility*




*Note: High financial frictions regimes are presented in red-like colors, while low ones are presented in blue-like colors. High monetary policy response regimes are presented in solid lines, while low ones are presented in dashed lines. High volatility regimes have the darkest colors, medium mild tones, and low ones are in the lightest tones.*

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