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Conservatorship, quantitative easing, and mortgage spreads: A new multi-equation score-driven model of policy actions

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Abstract: This paper studies how United States (US) policy actions impacted mortgage-backed securities (MBS) investors and mortgage borrowers during the subprime mortgage crisis of 2007 to 2010. The effects of the following policy actions on MBS spreads and mortgage lending spreads are studied: (i) US Government conservatorship of Fannie Mae and Freddie Mac; (ii) US Federal Reserve quantitative easing (QE) programs. We provide the following contributions: (i) The novel multi-equation score-driven t-QVARMA (quasi-vector autoregressive moving average) model of the multivariate t-distribution is used for the robust measurement of policy effects. (ii) In addition to the effects of QE, the effects of government conservatorship are also measured. (iii) The data period of the relevant literature is extended to March 2020, which provides a larger sample size for the pre-crisis and post-crisis periods. The results indicate that both policy actions significantly reduced MBS and mortgage lending spreads.

Keywords: Government-sponsored enterprises; Quantitative easing; Conservatorship; Mortgage-backed securities; Dynamic conditional score; Generalized autoregressive score; United States

JEL Classification Codes: C32, C52, E52, E58, G21, G28

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1. Introduction

Fannie Mae and Freddie Mac, two United States (US) government-sponsored enterprises (GSEs), received the largest taxpayer bailout ever during the US subprime mortgage crisis. Those GSEs had been operating for many decades to multiply financial means, create liquidity for mortgage financing, and provide assistance to families through interest subsidy payments.

Fannie Mae and Freddie Mac were de facto nationalized in 2008, and they have been under the US Government's control since then. In this way, the US Government controls more than ninety percent of the US mortgage finance market (see, for example, Blazsek 2020). In this paper, we provide an empirical analysis of how US policy actions affected mortgage-backed securities (MBS) investors and mortgage borrowers during the US subprime mortgage crisis (2007-2010). In particular, we measure the effects of the following two policy actions on MBS and mortgage lending spreads.

The first policy action is the placement of Fannie Mae and Freddie Mac into government conservatorship. While market participants had assumed an implicit guarantee by the US Government over the securities guaranteed by the GSEs and their debt, conservatorship changed this implicit guarantee into an explicit guarantee. The policy action, announced on September 6, 2008, intended to (i) stabilize the financial condition (i.e. by reducing their losses) and operational and credit risks; (ii) keep mortgage borrowing costs affordable for mortgage loan borrowers, as GSE-guaranteed MBS investors could rely on the US Government with respect to credit losses from mortgage delinquencies and defaults.

The second policy action involves the Federal Reserve (hereinafter, Fed) quantitative easing (QE) programs. Prompted by the bankruptcy of Lehman Brothers in September 2008 and the subsequent financial panic, to keep long-term interest rates low and make borrowing affordable the Federal Open Market Committee (FOMC) lowered the short-term federal funds rate to 0.25%, i.e. it was set near to the zero lower bound. Taylor rule-based calculations (Taylor 1993) would have implied a negative federal funds rate for September 2008. Due to the fact that the Fed was constrained by the zero lower bound for the federal funds rate, policy-makers decided that unconventional new tools (i.e. involving the QE programs) of monetary policy were to be used in order to stabilize the US economy.

QE consisted of several programs (Williams 2011; Fleming 2012; Carpenter et al. 2015; Bhar et al. 2015; Wang 2019): (i) The first large-scale asset purchase (LSAP) program was announced on November 25, 2008 (Federal Reserve 2008), stating that the Fed would buy up to USD 100 billion GSE debt, and up to USD 500 billion GSE MBS. The first LSAP program was conducted in the period of

November 2008 to June 2010 (Carpenter et al. 2015). (ii) The second LSAP program was conducted in the period of November 2010 to June 2011 (Carpenter et al. 2015) and involved the purchase of USD 600 billion of US Treasury bonds, mostly with 2- to 10-year maturities. (iii) The maturity extension program (MEP), also named Operation Twist (first attempted in 1961), was conducted in the period of September 2011 to December 2012 (Carpenter et al. 2015) and under it the FOMC purchased USD 400 billion of US Treasury bonds with remaining maturities of 6 to 30 years while simultaneously selling an equal amount of Treasuries with remaining maturities of 3 years or less. (iv) The reinvestment program for the proceeds of maturing and prepaying mortgage-backed securities was conducted in the period of August 2010 to December 2012 (Carpenter et al. 2015). (v) The Fed announced its intention to purchase an additional USD 40 billion per month GSE MBS in September 2012. This monthly amount was increased by an additional USD 45 billion per month of purchases of US Treasury bonds in December 2012. The monthly amount of USD 85 billion of purchases of those assets continued during 2013, and it was gradually terminated during the 10 months before October 2014 (Bhar et al. 2015).

In a recent work, Hamilton (2018) concludes that it is difficult to precisely estimate the effects of QE, and that the significance of those effects is probably smaller than many practitioners believe. As noted in the work of Guirguis and Trieste (2020), the limited sample size that is used in most of the papers of the literature implies the use of single-equation methods to study the effects of unconventional monetary policy on US Treasury yields and mortgage rates for the period of the US subprime mortgage crisis. Motivated by these points, we provide the following contributions to the literature:

The first contribution of this paper is the use of the novel multi-equation score-driven t-QVARMA (quasi-vector autoregressive moving average) model with exogenous explanatory variables, extending the model of Blazsek et al. (2019). The t-QVARMA model is a robust score-driven state space model (Creal et al. 2008; Harvey and Chakravarty 2008), which uses the multivariate t-distribution for the error term and is robust to outliers and missing observations, with a statistical performance superior to the statistical performances of the classical VAR and VARMA models (Blazsek et al. 2019). In our multi-equation model, co-integrated MBS spreads and mortgage lending spreads are used as dependent variables, and the model includes several exogenous explanatory variables, two of which measure the effects of the aforementioned policy actions, and the remaining explanatory variables control for relevant economic conditions (Chen et al. 2012; Guirguis and Trieste 2020).

The second contribution of this paper is that, in addition to QE, we also study the effects of government conservatorship on mortgage spreads. Several works study the effects of QE on US Treasury yields and mortgage rates (e.g. Gagnon et al. 2011; Krishnamurthy et al. 2011; Hancock and Passmore 2011, 2012), but to our knowledge the effects of conservatorship on those variables are not measured in the literature. Further, to our knowledge, in the body of literature all works related to US Government conservatorship provide descriptive analyses of the first policy action (i.e. Fannie Mae and Freddie Mac). In the present paper, we estimate the effects of both policy actions (i.e. Fannie Mae and Freddie Mac; Fed QE) on mortgage spreads, by using the t-QVARMA model.

The third contribution of this paper is that we extend the data period of literature until March 2020, for which we are able to separate pre- and post-US subprime mortgage crisis periods by using a relatively large sample size, providing robust empirical results.

For the period of June 1998 to March 2020, we use mortgage spreads, rather than US Treasury bond yields and mortgage rates, motivated by the works of Stroebel and Taylor (2012), Boyarchenko et al. (2019), and Wang (2019). We separately fit the econometric model for mortgage spreads, which represent spreads on GSE-guaranteed MBS that indicate investors' expected excess return over US Treasury yields, and for mortgage lending spread, defined as the borrowing cost on the top of US Treasury yields faced by home-buyers or homeowners. The main difference between these investor categories is that GSE-guaranteed MBS investors do not face credit risk, but refinancing, liquidity, and interest rate risks. Nonetheless, mortgage borrowers, although their homes serve as a collateral, are a credit risk to the GSEs. The robust empirical results of this paper indicate that both policy actions significantly reduced the MBS spreads and mortgage lending spreads in the US.

The remainder of this paper is organized as follows: Section 2 reviews the relevant literature on conservatorship, QE, and score-driven models. Section 3 presents the t-QVARMA model and its statistical inference. Section 4 presents the data and the empirical results. Section 5 concludes.

2. Review of the literature

2.1. First policy action: conservatorship of Fannie Mae and Freddie Mac

In the work of Kaufman (2012), it is reported that the Housing and Economic Recovery Act (HERA) of 2008 replaced the regulator Office of Federal Housing Enterprise Oversight (OFHEO) with the Federal Housing Finance Agency (FHFA), and granted it the power to place the GSEs into conservatorship, which the FHFA did in late 2008, finally explicitizing the guarantee of the government's long-standing implicit backing/guarantee of GSE debt. Since then the GSEs have been held in conservatorship out of concern that their deteriorating financial conditions would destabilize the financial system.

Frame et al. (2015) review the rescue via conservatorship of Fannie Mae and Freddie and present firms' business models, the sources of the financial distress experienced by both firms during the 2008 US financial crisis, and the various resolution actions available to US policymakers. The authors also evaluate the success of the use of conservatorship and conclude that it achieved its short-run success, by stabilizing mortgage markets and promoting financial stability within the crisis period.

In the review article of Jaffee and Quigley (2013) the following issues are presented: (i) background and origin of the GSEs, (ii) evolution of their structure as a public/private partnership, and the federal role in supplying housing credit, (iii) the failures of the credit market and the secondary housing market during the US subprime mortgage crisis, (iv) the likely consequences of a series of plans concerning the restructuring of the GSEs, and alternative mechanisms for government support of the US mortgage market, (v) a brief summary of the GSEs under their government conservatorship since September 2008, and (vi) possible future scenarios for Fannie Mae and Freddie Mac.

Hacock and Passmore (2011) report that on September 7, 2008, the FHFA placed Fannie Mae and Freddie Mac into conservatorship. At the same time, the US Treasury took additional steps to complement the FHFA's decision to place both enterprises into conservatorship. The US Treasury and the FHFA established preferred stock purchase agreements, i.e. contractual agreements between the US Treasury and the GSEs, to ensure that each company would maintain a positive net worth. In the work of Barth et al. (2009), the specific terms of the preferred stock purchase agreements are presented. Moreover, the US Treasury established a new secured lending credit facility that was available to Fannie Mae, Freddie Mac, and the Federal Home Loan Banks. Jaffee (2010) reports that, for the period of September 2008 to September 2009, Fannie Mae and Freddie Mac required capital infusions of USD 111 billion from the US Treasury, in order to set the capital accounts back to zero.

In the work of An and Bostic (2009), the authors conclude that their results have important implications for how GSEs should operate in a post-conservatorship environment. Although the GSEs entered conservatorship due to exposures to risk associated with subprime and other nonconforming mortgages, much of those exposures were from purchases of loans originated in a more permissive underwriting environment than the purchases of loans which prevailed during the study period of An and Bostic (2009). The authors suggest that if GSE and broader market standards were to return to their 1990s levels, a repeat of the GSE problems experienced during the US subprime mortgage crisis, associated with engaging more risky segments of the mortgage market, should not be expected.

These works are descriptive studies of conservatorship, in which specific details of the first policy action are presented, but the effects of conservatorship on the mortgage market are not measured. This motivates the use of the convervatorship dummy explanatory variable in the t-QVARMA model of the present paper, to measure the effects of the first policy action on mortgage spreads.

2.2. Second policy action: quantitative easing (QE)

Several works study the impact of QE on US Treasury bond yields. We classify some of those works with respect to research methods as follows: (i) Event studies are used in the works of Doh (2010), Meaning and Zhu (2011), Christensen and Rudebusch (2012), D'Amico et al. (2012), D'Amico and King (2013), Foerster and Cao (2013), Bauer and Rudebusch (2014), and Neely (2015). (ii) Affine term structure models are used in the works of Christensen and Rudebusch (2012), Hamilton and Wu (2012), Li and Wei (2013), and Bauer and Rudebusch (2014). (iii) Time series models are used in the works of Chen et al. (2012), D'Amico et al. (2012), and Bhar et al. (2015).

Several works study the impact of QE on GSE MBS yields, mortgage lending rates, and the corresponding spreads over US Treasury bond yields. We classify some of those works with respect to research methods as follows: (i) Event studies are used in the works of Gagnon et al. (2011), Swanson et al. (2011), and Guirguis and Trieste (2020). (ii) A MBS asset pricing model is used in the work of Boyarchenko et al. (2019). (iii) Time series models are used in the works of Gagnon et al. (2011), Hancock and Passmore (2011, 2012), Krishnamurthy et al. (2011), Stroebel and Taylor (2012), Miles (2014), and Guirguis and Trieste (2020). (iv) A micro-level panel data model is used in the work of Wang (2019). The findings of some of those works are briefly summarized as follows:

In the work of Gagnon et al. (2011), the authors find that, as a consequence of the first LSAP program, the 10-year US Treasury yield declined by 91 basis points, the 10-year GSE debt yields declined by 156 basis points, and the average of the Freddie Mac and Fannie Mae current-coupon 30-year MBS yield declined by 113 basis points. Hence, the authors find that GSE debt spreads decreased by 65 basis points, and MBS spreads declined by 22 basis points.

In the work of Krishnamurthy et al. (2011), for the first LSAP program, the authors find that the 10-year US Treasury yield declined by 100 basis points, the 10-year GSE debt yields declined by 164 basis points, and the average of the Ginnie Mae, Freddie Mac, and Fannie Mae current-coupon 30-year MBS yield declined by 116 basis points. Hence, the authors find that GSE debt spreads declined by 64 basis points, and MBS spreads declined by 16 basis points. Moreover, for the second LSAP program, the authors find that the 10-year US Treasury yield declined by 25 basis points, and the 10-year GSE debt yield declined by 27 basis points. Hence, the authors find a small decrease in the GSE debt spreads for the second LSAP program.

In the works of Hancock and Passmore (2011, 2012), the authors find that the Fed's LSAP programs significantly reduced the MBS rates and the mortgage lending rates.

On the other hand, Swanson et al. (2011) find that Operation Twist lowered the US Treasury yield curve by about 15 basis points, and it lowered GSE lending yields by about 13 basis points. Hence, the authors find a slight increase in the GSE lending spreads. Stroebel and Taylor (2012) find no significant decrease in MBS spreads as a result of the first LSAP program. Furthermore, in the work of Boyarchenko et al. (2019), the effects of the Fed's first LSAP program on MBS spreads are studied. The authors suggest a MBS pricing model, which explains the empirically observed decreases in the lower-coupon MBS spreads, and increases in the higher-coupon MBS spreads, after the announcement of the first LSAP program on November 25, 2008.

In the work of Wang (2019), by using using micro-level MBS deals data for the period of 2007 to 2017, the author finds that unconventional monetary policy had a significant negative impact on MBS spreads. The author argues that MBS spreads represent the compensation for credit, prepayment, and liquidity risks of MBS investors. Furthermore, the mortgage lending spread represents the compensation for credit, refinancing, liquidity, and interest rate risks of mortgage borrowers.

In the recent work of Guirguis and Trieste (2020), the authors study the impact of unconventional monetary policy on mortgage rates. The authors highlight that several works of the relevant literature use limited sample sizes, which do not allow the use of econometric methods more complex than single-equation methods. The authors contribute to the literature, by using the shadow federal funds rate (Wu and Xia 2016) for the period of the near zero short-term federal funds rate, which provides a larger sample size for the empirical analysis. This allows the authors to use a multi-equation VAR model that includes several macroeconomic variables for the period of May 1971 to September 2017, in order to reach more reliable conclusions about the effects of unconventional monetary policy on mortgage rates. The authors find negative effects of LSAPs on mortgage spreads.

From these works, those most relevant to our paper are Stroebel and Taylor (2012), Boyarchenko et al. (2019), and Wang (2019), because they motivate the use of mortgage spreads. The work of

Guirguis and Trieste (2020) is also relevant, because it motivates the use of the multi-equation t-QVARMA model, to reach reliable conclusions about the effects of unconventional monetary policy as in the present work.

2.3. Score-driven time series models

For the analysis of monetary policy actions by using score-driven time series models, we refer to the recent work of Caballero et al. (2020), in which the authors study the time-variation in central bank portfolio credit risks associated with unconventional monetary policy operations. The authors apply score-driven copula models, to provide empirical measures of portfolio credit risk at the European Central Bank (ECB). In the present paper, we use a different multi-equation score-driven model, named t-QVARMA, in which the co-movement of dependent variables is captured by the idea of co-integration.

Score-driven time series models are introduced in the works of Creal et al. (2008), and Harvey and Chakravarty (2008). Score-driven models are observation-driven (Cox 1981) state space models, which are applied to study variables with different orders of integration, e.g. $I(0)$, $I(1)$, or fractional integration (Hamilton 1994). An advantage of score-driven models is that they implement optimal filtering mechanisms, according to the Kullback–Leibler divergence with respect to the true data generating process. In the work of Blasques et al. (2015) asymptotic results are presented, for which it is shown that a score-driven update of the model reduces the Kullback–Leibler divergence in expectation and at every step, and those authors also show that only score-driven updates can have this property. We also refer to the recent work of Blasques et al. (2020), in which the filtering mechanisms of score-driven models for finite samples are supported. A further advantage of score-driven models is that they are more robust to extreme observations and missing data than classical time series models (Harvey 2013).

The "DCS model for the multivariate t-distribution" (Harvey 2013, p. 210) is an alternative to the VARMA model (Tiao and Tsay 1989). The model of Harvey (2013) can be applied to $I(0)$ variables or co-integrated $I(1)$ variables (Granger 1981; Engle and Granger 1987). In the work of Creal et al. (2014), the score-driven t-QVARMA model is introduced for $I(0)$ variables. In the recent work of Blazsek et al. (2019) the t-QVARMA model is extended to combinations of $I(0)$ and co-integrated $I(1)$ variables, which is further extended in the present work to include exogenous explanatory variables.

3. Econometric model

3.1. Multi-equation score-driven model: t-QVARMA

The reduced-form representation of the first-order t-QVARMA model for the dependent variables y_t $(K \times 1)$ with $t = 1 \ldots, T$, which are assumed to be $I(1)$ and co-integrated, is given by:

$$y_t = \mu_t + v_t = \mu_t^* + \mu_t^\dagger + \mu_t^\circ + v_t \tag{1}$$

$$\mu_t^* = \Phi^* \mu_{t-1}^* + \Psi^* u_{t-1} \tag{2}$$

$$\mu_t^\dagger = \mu_{t-1}^\dagger + \Psi^\dagger u_{t-1} \tag{3}$$

$$\mu_t^\circ = \Psi^\circ Z_t \tag{4}$$

$$v_t \sim t_K(0_{K\times 1}, \Sigma, \nu) = t_K[0, \Omega^{-1}(\Omega^{-1})', \nu] \text{ i.i.d.} \tag{5}$$

where Φ^* $(K \times K)$, Ψ^* $(K \times K)$, $\Psi^\dagger$ $(K \times K)$, Ψ° $(K \times R)$ Ω^{-1} $(K \times K)$, and ν are constant parameters.

Vector μ_t^* $(K \times 1)$ includes $I(0)$ variables, vector $\mu_t^\dagger$ $(K \times 1)$ includes co-integrated $I(1)$ variables, and vector μ_t° $(K \times 1)$ includes exogenous explanatory variables, denoted as Z_t $(R \times 1)$. In this way, y_t is decomposed into $I(0)$ and $I(1)$ components, similarly to the Granger-representation of the VAR model (e.g. Johansen 1995). For the first observation of the sample, μ_t^* is initialized by using $E(\mu_t^*) = 0_{K\times 1}$. For the first observation of the sample, $\mu_t^\dagger$ is initialized by estimating the parameter vector $\mu_{0,1}^\dagger$ $(K \times 1)$. Variable u_t $(K \times 1)$ is the scaled score function, and it is defined in the next section.

Motivated by the work of Creal et al. (2014), we assume that Φ^* and Ψ^* are diagonal matrices, in order to identify the $I(0)$ component μ_t^*. We assume that the rank of matrix $\Psi^\dagger$ is one, i.e. there is one common factor in the $I(1)$ component $\mu_t^\dagger$. Furthermore, all elements of Ψ° are estimated.

The reduced-form error term v_t has a multivariate t-distribution with zero mean vector, scale matrix Σ, and degrees of freedom parameter ν. The positive-definite matrix Σ is estimated by using the decomposition $\Omega^{-1}(\Omega^{-1})'$, where Ω^{-1} is a lower-triangular matrix, and the degrees of freedom parameter ν is jointly estimated with the rest of the parameters.

The conditional mean vector of the dependent variables is: $E(y_t|y_1, \ldots, y_{t-1}; \Theta) \equiv E(y_t|\mathcal{F}_{t-1}; \Theta) = \mu_t = \mu_t^* + \mu_t^\dagger + \mu_t^\circ$, where $\Theta = (\Theta_1, \ldots, \Theta_S)'$ is the vector of time-invariant parameters. The elements of Θ are defined by using the elements of Φ^*, Ψ^*, $\Psi^\dagger$, Ψ°, Ω^{-1}, ν, and $\mu_{0,1}^\dagger$.

3.2. Scaled score function

The log conditional density function of $y_t|\mathcal{F}_{t-1}$ is

$$\ln f(y_t|\mathcal{F}_{t-1};\Theta) = \ln\Gamma\left(\frac{\nu+K}{2}\right) - \ln\Gamma\left(\frac{\nu}{2}\right) - \frac{K}{2}\ln(\pi\nu) \tag{6}$$

$$-\frac{1}{2}\ln|\Sigma| - \frac{\nu+K}{2}\ln\left(1+\frac{v_t'\Sigma^{-1}v_t}{\nu}\right)$$

The partial derivative of the log conditional density with respect to μ_t is

$$\frac{\partial \ln f(y_t|\mathcal{F}_{t-1};\Theta)}{\partial\mu_t} = \frac{\nu+K}{\nu}\Sigma^{-1}\times\left(1+\frac{v_t'\Sigma^{-1}v_t}{\nu}\right)^{-1} v_t \equiv \frac{\nu+K}{\nu}\Sigma^{-1}\times u_t \tag{7}$$

which defines the scaled score function u_t, by using the reduced-form error term v_t (Harvey 2013, p. 210). In the definition of u_t, the reduced-form error term v_t is multiplied by $[1+(v_t'\Sigma^{-1}v_t)/\nu]^{-1} = \nu/(\nu+v_t'\Sigma^{-1}v_t)\in(0,1)$. Hence, u_t is bounded by the reduced-form error term: $|u_t|<|v_t|$. In the work of Harvey (2013, p. 211 and p. 206), it is shown that the scaled score function u_t is multivariate i.i.d. with mean zero, and the following well-defined covariance matrix:

$$\mathrm{Var}(u_t) = E\left[\frac{\partial \ln f(y_t|\mathcal{F}_{t-1};\Theta)}{\partial\mu_t}\times\frac{\partial \ln f(y_t|\mathcal{F}_{t-1};\Theta)}{\partial\mu_t'}\right] = \frac{\nu+K}{\nu+K+2}\Sigma^{-1}. \tag{8}$$

3.3. Statistical inference

The parameters of t-QVARMA are estimated by using the maximum likelihood (ML) method:

$$\hat{\Theta}_{\mathrm{ML}} = \arg\max_{\Theta}\mathrm{LL}(y_1,\ldots,y_T;\Theta) = \arg\max_{\Theta}\sum_{t=1}^{T}\ln f(y_t|\mathcal{F}_{t-1};\Theta) \tag{9}$$

The standard errors of $\hat{\Theta}_{\mathrm{ML}}$ are estimated by using the inverse information matrix (Blazsek et al. 2019). The ML conditions for the t-QVARMA model with $\mu_t^{\circ}=0_{K\times1}$ are proven in the work of Blazsek et al. (2019). For the t-QVARMA model of the present paper those conditions are extended, by using the maintained assumption that all explanatory variables in Z_t are strictly exogenous (Harvey 2013).

For component μ_t^*, the empirical estimates of the following conditions are reported in the following section of this paper: The first condition is the covariance stationarity of μ_t^*, for which it is required that the maximum modulus of eigenvalues of Φ^*, denoted by C_1, is less than one.

The second condition is the negative Lyapunov exponent for μ_t^*, which is given by:

$$\inf_{n\geq 1}\left\{n^{-1}E\left[\ln\left|\left|\prod_{t=1}^{n}\frac{\partial\mu_t^*}{\partial(\mu_{t-1}^*)'}\right|\right|_1\right]\right\}=\inf_{n\geq 1}\left\{n^{-1}E\left(\ln\left|\left|\prod_{t=1}^{n}\Phi^*+\Psi^*\frac{\partial u_{t-1}}{\partial(\mu_{t-1}^*)'}\right|\right|_1\right)\right\}<0 \tag{10}$$

(Straumann and Mikosch 2006), where the matrix norm $||A||_1=\max_{1\leq j\leq K}\sum_{i=1}^{K}|a_{i,j}|$ is used, with $A=\{a_{i,j}\}$ for $i,j=1,\ldots,K$. The empirical estimate of this condition is denoted by C_2.

The third condition is for the following derivatives in the ML gradient (Harvey 2013):

$$\frac{\partial\mu_t^*}{\partial\Psi_{i,j}^*}=\Phi^*\frac{\partial\mu_{t-1}^*}{\partial\Psi_{i,j}^*}+\Psi^*\frac{\partial u_{t-1}}{\partial\Psi_{i,j}^*}+W_{i,j}u_{t-1} \tag{11}$$

$$\frac{\partial\mu_t^*}{\partial\Psi_{i,j}^*}=\left[\Phi^*+\Psi^*\frac{\partial u_{t-1}}{\partial(\mu_{t-1}^*)'}\right]\frac{\partial\mu_{t-1}^*}{\partial\Psi_{i,j}^*}+W_{i,j}u_{t-1}\equiv X_t\frac{\partial\mu_{t-1}^*}{\partial\Psi_{i,j}^*}+W_{i,j}u_{t-1} \tag{12}$$

for $i,j=1,\ldots,K$; $W_{i,j}$ is a $(K\times K)$ matrix, in which element (i,j) is one and the rest of the elements are zero. According to the condition, the maximum modulus of eigenvalues of $E(X_t)$, denoted by C_3, is less than one. The same condition is obtained, when the derivative with respect to $\Phi_{i,j}^*$ is considered.

The fourth condition is for the following derivatives in the information matrix (Harvey 2013):

$$\frac{\partial\mu_t^*}{\partial\Psi_{i,j}^*}\frac{\partial(\mu_t^*)'}{\partial\Psi_{k,l}^*}=X_t\frac{\partial\mu_{t-1}^*}{\partial\Psi_{i,j}^*}\frac{\partial(\mu_{t-1}^*)'}{\partial\Psi_{k,l}^*}X_t'+X_t\frac{\partial\mu_{t-1}^*}{\partial\Psi_{i,j}^*}(u_{t-1})'W_{i,j}' \tag{13}$$

$$+W_{k,l}u_{t-1}\frac{\partial(\mu_{t-1}^*)'}{\partial\Psi_{k,l}^*}X_t'+W_{i,j}u_{t-1}(u_{t-1})'W_{k,l}'$$

which, by using the Kronecker product $\otimes$, can be written as:

$$\text{vec}\left[\frac{\partial\mu_t^*}{\partial\Psi_{i,j}^*}\frac{\partial(\mu_t^*)'}{\partial\Psi_{k,l}^*}\right]=(X_t\otimes X_t)\text{vec}\left[\frac{\partial\mu_{t-1}^*}{\partial\Psi_{i,j}^*}\frac{\partial(\mu_{t-1}^*)'}{\partial\Psi_{k,l}^*}\right]+\text{vec}\left[X_t\frac{\partial\mu_{t-1}^*}{\partial\Psi_{i,j}^*}(u_{t-1})'W_{i,j}'\right] \tag{14}$$

$$+\text{vec}\left[W_{k,l}u_{t-1}\frac{\partial(\mu_{t-1}^*)'}{\partial\Psi_{k,l}^*}X_t'\right]+\text{vec}\left[W_{i,j}u_{t-1}(u_{t-1})'W_{k,l}'\right]$$

According to the condition, the maximum modulus of eigenvalues of $E(X_t\otimes X_t)$, denoted by C_4, is less than one. The same condition is obtained when the derivative with respect to $\Phi_{i,j}^*$ is considered.

For $\mu_t^\dagger$ the asymptotic theory for the ML estimator holds, because the first-order dynamic parameter matrix is set to the identity matrix in Equation (3) (Harvey 2013).

4. Empirical results

4.1. Data

Monthly data for the period of June 1998 to March 2020 are used, to separate pre-US subprime mortgage crisis and post-US subprime mortgage crisis periods (source of data: Bloomberg).

For the first set of dependent variables, data for the following MBS spreads are used: (M1) Fannie Mae MBS spread (30-year Fannie Mae MBS current coupon rate minus 10-year US Treasury yield). (M2) Freddie Mac MBS spread (30-year Freddie Mac MBS current coupon rate minus 10-year US Treasury yield). (M3) Ginnie Mae MBS spread (30-year Ginnie Mae MBS current coupon rate minus 10-year US Treasury yield). These spreads are calculated by using variables with the following Bloomberg tickers: MTGEFNCL Index, MTGEFHLM Index, MTGEGNSF Index, and GT10 Govt.

For the second set of dependent variables, data for the following mortgage lending spreads are used: (L1) Freddie Mac survey lending spread (Freddie Mac US Mortgage Market Survey 30-Year Homeowner Commitment Rate minus 10-year US Treasury yield). (L2) 30-year fixed lending spread (Bankrate.com US Home Mortgage 30-year Fixed National Average minus 10-year US Treasury yield). Note that (L1) and (L2) are similar, and indicative of the spread for GSE-guaranteed mortgage borrowers. (L3) Jumbo lending spread (Bankrate.com US Home Mortgage 30-Year Jumbo National Average minus 10-year US Treasury yield), which represents the spread faced by borrowers that are not guaranteed by the GSEs. These spreads are calculated by using variables with the following Bloomberg tickers: NMCMFUS Index, ILM3NAVG Index, ILMJNAVG Index, and GT10 Govt.

As aforementioned, variables (M1) Fannie Mae MBS spread, (M2) Freddie Mac MBS spread, and (M3) Ginnie Mae MBS spread are relevant for MBS investors, whereas variables (L1) Freddie Mac lending spread, (L2) fixed lending spread, and (L3) jumbo lending spread are relevant for mortgage borrowers and lenders. Therefore, two three-dimensional multi-equation models are estimated, which include variables (M1) to (M3) and (L1) to (L3), respectively. All dependent variables are measured in percentage points, and their evolution for the sample period is presented in Figure 1.

We note that MBS spreads, as defined by (M1) to (M3), are called nominal spreads by MBS investors. While preferring the use of the 10-year US Treasury bonds to 30-year US Treasury bonds may not seem intuitive at first sight, loans in the MBS pools have the tendency to prepay before maturity because of refinancing when interest rates decline and due to housing turnover, as shown by prepayment statistics published by FHFA. Thus, calculating nominal spread relative to the 10-year US

Treasury yield is a conventional choice. We refer to the works of Hu (2011) and Chernov et al. (2018).

We acknowledge that nominal spreads contain an option premium to the MBS investors, in order to compensate for the refinancing risk. Option-adjusted spreads (OASs) thus are widely used to clear nominal spread from the option premium. However, during the heights of the crisis, refinancing was very difficult for most of the borrowers, as house prices collapsed and banks' lending standards suddenly became very strict. As a result, OASs generated by different models differed significantly from each other during 2008 and 2009, so we believe that nominal spread is the cleanest choice (we control for the impact of optionality with a careful choice of the explanatory variables).

For explanatory variables, data from the following variables are used: (E1) 3-month US Treasury yield, which approximates the level of interest rates in the US, and it also indicates the period of the unconventional monetary policy (Bloomberg ticker: GB3 Govt). (E2) ICE Bank of America MOVE index that represents the future volatility in US Treasury yields, implied by the option prices on US Treasury bonds of various maturities. We use this variable to capture general interest rate market volatility that has an impact on the value of the refinancing option (Bloomberg ticker: MOVE Index). (E3) Fed System's Open Market Account Agency MBS holding. This variable quantifies the Fed's MBS holding under the QE programs (Bloomberg ticker: SOMHAMBS Index). (E4) GSE MBS market capitalization, which is approximated by the Bloomberg Barclays US MBS Market Capitalization Index (Bloomberg ticker: LUMSTRUU Index). Thus, (E4) is indicative of the total MBS supply available to investors, and (E3) shows how much supply the Fed is taking out of the market. (E5) Conservatorship dummy, which takes the value one for the period of September 2008 to March 2020, and zero otherwise. Variables (E1) and (E2) are measured in percentage points, variables (E3) and (E4) are measured in USD trillion, and the evolution of (E1) to (E4) is presented in Figure 2.

In addition, we also considered the use of the following explanatory variables, which finally were excluded from the econometric specifications: (E6) 10-year US Treasury yield (Bloomberg ticker: GT10 Govt), to measure the yield levels of long-term Treasury bonds. Nevertheless, from the final specification this variable is excluded due to endogeneity, as it is part of the MBS and mortgage lending spreads. (E7) 10-year interest rate swap spread (Bloomberg ticker: USSP10 Index), which is the difference between the fixed rate of a 10-year interest rate swap agreement and the 10-year US Treasury yield. We consider this variable to quantify general market liquidity and approximate banking credit risk. However, this variable is also excluded from the final specification due to endogeneity. The evolution of variables (E6) and (E7) is presented in Figure 2. (E8) Delinquency rate on single-family residential mortgages (source: Federal Reserve Economic Data, ticker: DRSFRMACBS). This variable indicates the credit conditions in the mortgage lending market. However, this variable is also excluded from the final specification, because its observation frequency is not monthly, and we could not find an alternative variable on delinquency rate for monthly observation frequency for the sample period.

We believe that the choice of variables is sufficiently comprehensive to capture general economic conditions that would typically impact GSE MBS and mortgage lending spreads. The explanatory variables also cover the policy actions that are within the focus of our research. Our choosing these explanatory variables can be compared to the choice in the work of Harrison at al. (2012), in which a broader range of explanatory variables specific to distinct mortgage products are used. Nevertheless, the explanatory variables of Harrison at al. (2012) do not include regulatory and policy variables.

Descriptive statistics for the dependent and explanatory variables, and their percentage changes, are presented in Table 1. The order of integration for each variable is also studied in Table 1, by using the augmented Dickey–Fuller (Dickey and Fuller 1979) test, and by using the order of fractional integration estimator of Geweke and Porter-Hudak (1983). The order of fractional integration estimates suggests that dependent and explanatory variables are $I(1)$, and their percentage changes are $I(0)$.

Co-integration relationships are tested by using the trace and the maximum eigenvalue tests of Johansen (1988, 1991, 1995). For those tests, v_t ($K \times 1$) has a multivariate normal distribution in the following VECM (vector error correction model) representation of the VAR(p) model for y_t ($K \times 1$):

$$\Delta y_t = \Pi y_{t-1} + \Gamma_1 \Delta y_{t-1} + \ldots + \Gamma_{p-1} \Delta y_{t-p+1} + v_t \tag{15}$$

where Π ($K \times K$), $\Gamma_1, \ldots, \Gamma_{p-1}$ (each $K \times K$) are time-invariant parameters. The co-integration test results are presented in Table 2. According to the trace and the maximum eigenvalue tests, (M1) to (M3) are co-integrated with one common stochastic trend ($K = 3$). According to the maximum eigenvalue test, (L1) to (L3) are co-integrated with one common stochastic trend ($K = 3$). These results influence the specification of $\mu_t^{\dagger}$ in t-QVARMA. The Johansen test results indicate that co-integration is less significant for (L1) to (L3) than for (M1) to (M3). According to the trace and the maximum eigenvalue tests, (M1) to (M3) and (E1) to (E4) are co-integrated ($K = 7$). According to the trace and the maximum eigenvalue tests, (L1) to (L3) and (E1) to (E4) are co-integrated ($K = 7$).

Table 1. Descriptive statistics for the period of June 1998 to March 2020 ($T = 262$)

Dependent variables (level)	Min	Max	Mean	SD	Skew	Kurtosis	SW	ADF const	ADF trend	GPH(SE)
(M1) 30-year Fannie Mae MBS spread	0.2060	2.0800	1.0715	0.3745	0.6684	−0.3943	0.9352***	−2.4554+	−3.6233**	0.9328(0.2225)
(M2) 30-year Freddie Mac MBS spread	0.2270	2.1510	1.1040	0.3767	0.6669	−0.3223	0.9406***	−2.3641	−3.9310**	0.9087(0.2027)
(M3) 30-year Ginnie Mae MBS spread	0.2120	2.0960	0.9507	0.4055	0.6011	−0.6678	0.9371***	−2.2012	−3.6390**	0.9515(0.2157)
(L1) 30-year Freddie Mac lending spread	1.1620	3.0480	1.8109	0.2842	1.1788	2.2984	0.9310***	−4.9571***	−4.9520***	0.7554(0.3205)
(L2) 30-year fixed lending spread	0.9110	3.1900	1.6602	0.3405	0.7371	2.0879	0.9624***	−2.5733*	−2.8524	0.8506(0.1840)
(L3) 30-year jumbo lending spread	1.1710	4.7460	2.1164	0.5727	1.3016	2.7047	0.9167***	−2.6932*	−2.7849	1.0264(0.2096)
Dependent variables (% change)	Min	Max	Mean	SD	Skew	Kurtosis	SW	ADF const	ADF trend	GPH(SE)
(M1) 30-year Fannie Mae MBS spread	−0.7151	1.5437	0.0093	0.1454	4.2174	49.4657	0.6814***	−14.7561***	−14.7504***	−0.0132(0.2078)
(M2) 30-year Freddie Mac MBS spread	−0.7215	1.1410	0.0066	0.1279	2.3236	27.6289	0.7665***	−14.4244***	−14.3986***	−0.1625(0.1768)
(M3) 30-year Ginnie Mae MBS spread	−0.6950	0.6651	0.0082	0.1369	0.7063	5.8543	0.9072***	−14.7961***	−14.8141***	−0.3000(0.2151)
(L1) 30-year Freddie Mac lending spread	−0.2407	0.3171	0.0071	0.0990	0.4956	0.4822	0.9804***	−19.1759***	−19.1392***	−0.1636(0.2227)
(L2) 30-year fixed lending spread	−0.2124	0.2915	0.0071	0.0909	0.5574	0.4139	0.9728***	−15.7135***	−15.6928***	−0.1104(0.1496)
(L3) 30-year jumbo lending spread	−0.2176	0.3653	0.0067	0.0970	0.7981	1.1829	0.9649***	−16.0372***	−16.0118***	0.1793(0.2980)
Explanatory variables (level)	Min	Max	Mean	SD	Skew	Kurtosis	SW	ADF const	ADF trend	GPH(SE)
(E1) 3-month US Treasury yield	−0.0150	6.3890	1.8678	1.9224	0.7924	−0.7405	0.8472***	−1.6019	−2.1064	1.2992(0.2261)
(E2) MOVE Index	0.4616	2.1400	0.8957	0.3005	1.2151	2.2604	0.9202***	−4.2439***	−5.0149***	0.9584(0.1239)
(E3) Fed MBS holding	0.0000	1.7736	0.6884	0.7383	0.3473	−1.6188	0.7666***	−1.1061	−2.6123	1.1923(0.1596)
(E4) MBS market capitalization	1.5733	6.3420	4.0388	1.3945	−0.2499	−1.3918	0.9010***	−0.6049	−1.2887	0.9778(0.0473)
Explanatory variables (% change)	Min	Max	Mean	SD	Skew	Kurtosis	SW	ADF const	ADF trend	GPH(SE)
(E1) 3-month US Treasury yield	−6.0000	7.0000	0.0579	0.9340	0.9305	29.1735	0.4812***	−13.5403***	−13.5618***	−0.1055(0.2041)
(E2) MOVE Index	−0.2959	1.0243	0.0134	0.1736	1.8001	6.5600	0.8852***	−20.1318***	−20.0923***	0.0067(0.1619)
(E3) Fed MBS holding	−0.0440	8.3188	0.0485	0.5360	14.5229	220.6577	0.0706***	−12.0314***	−12.0082***	0.0640(0.0138)
(E4) MBS market capitalization	−0.0308	0.1196	0.0054	0.0123	3.0145	27.9199	0.8191***	−12.6092***	−12.9790***	0.6232(0.1516)

Notes: Minimum (Min); maximum (Max); average (Mean); standard deviation (SD); skewness (skew); excess kurtosis (kurt); Shapiro–Wilk test statistic (SW); augmented Dickey–Fuller test statistic (ADF); ADF test with constant (ADF const); ADF test with constant and linear trend (ADF trend); Geweke and Porter-Hudak (GPH) estimate of the order of fractional integration with standard error (SE) in parentheses. The null hypothesis of the Shapiro–Wilk test (Shapiro and Wilk 1965) is normal distribution. The null and alternative hypotheses of the ADF test are that the variable is $I(1)$ and $I(0)$, respectively. For the ADF test, the optimal lag-order is selected by using the Bayesian information criterion (BIC). For the GPH estimate, lag-order 16 is used which approximates $(T)^{1/2}$. $^{+}$, *, **, and *** indicate significance at the 15%, 10%, 5%, and 1% levels, respectively.

Table 2. Co-integration tests

rank of Π	Trace test (p-value)	rank of Π	Maximum eigenvalue test (p-value)
(S1) Fannie Mae MBS spread, (S2) Freddie Mac MBS spread, (S3) Ginnie Mae MBS spread			
0	32.7870(0.0212)	0	22.9260(0.0254)
1	9.8601(0.2970)	1	9.6487(0.2411)
2	0.2114(0.6457)	2	0.2114(0.6457)
(L1) Freddie Mac lending spread, (L2) Fixed lending spread, (L3) Jumbo lending spread			
rank of Π	Trace test (p-value)	rank of Π	Maximum eigenvalue test (p-value)
0	26.3990(0.1203)	0	20.3150(0.0639)
1	6.0841(0.6890)	1	5.9715(0.6227)
2	0.1126(0.7372)	2	0.1126(0.7372)
(S1) Fannie Mae MBS spread, (S2) Freddie Mac MBS spread, (S3) Ginnie Mae MBS spread, (E1) 3-month US Treasury yield, (E2) MOVE index, (E3) Fed MBS holding, (E4) MBS market capitalization index			
rank of Π	Trace test (p-value)	rank of Π	Maximum eigenvalue test (p-value)
0	171.2900(0.0000)	0	72.9820(0.0000)
1	98.3040(0.0311)	1	34.7390(0.1812)
2	63.5660(0.1417)	2	28.8870(0.1794)
3	34.6790(0.4699)	3	16.1510(0.6591)
4	18.5280(0.5376)	4	11.4530(0.6127)
5	7.0755(0.5752)	5	5.2039(0.7176)
6	1.8716(0.1713)	6	1.8716(0.1713)
(L1) Freddie Mac lending spread, (L2) Fixed lending spread, (L3) Jumbo lending spread, (E1) 3-month US Treasury yield, (E2) MOVE index, (E3) Fed MBS holding, (E4) MBS market capitalization index			
rank of Π	Trace test (p-value)	rank of Π	Maximum eigenvalue test (p-value)
0	195.3800(0.0000)	0	77.9080(0.0000)
1	117.4700(0.0005)	1	38.4810(0.0720)
2	78.9860(0.0067)	2	31.4840(0.0925)
3	47.5020(0.0524)	3	24.4730(0.1198)
4	23.0290(0.2527)	4	12.8610(0.4793)
5	10.1680(0.2729)	5	8.3499(0.3522)
6	1.8179(0.1776)	6	1.8179(0.1776)

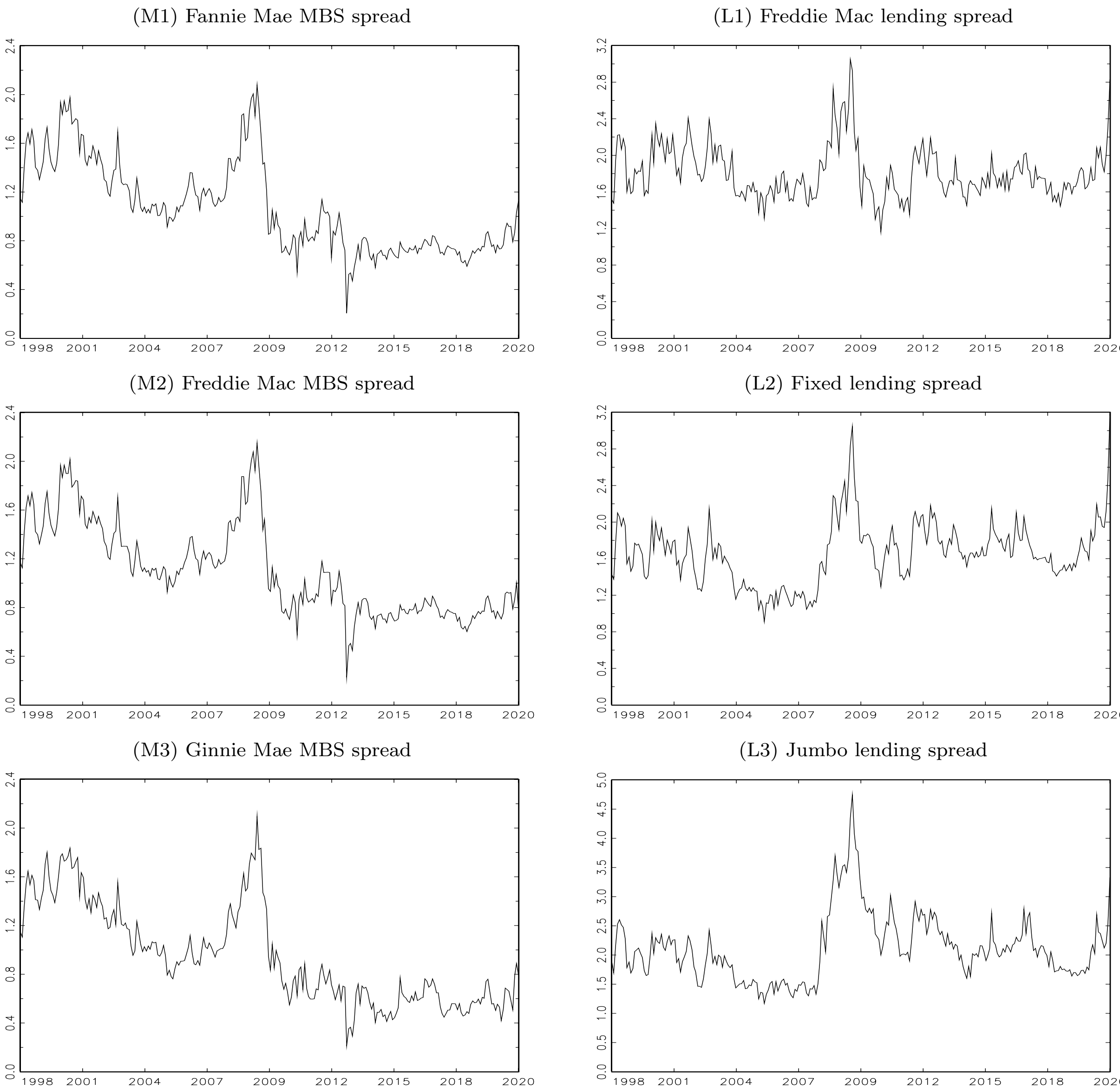

Figure 1. MBS spreads and lending spreads for the period of June 1998 to March 2020.

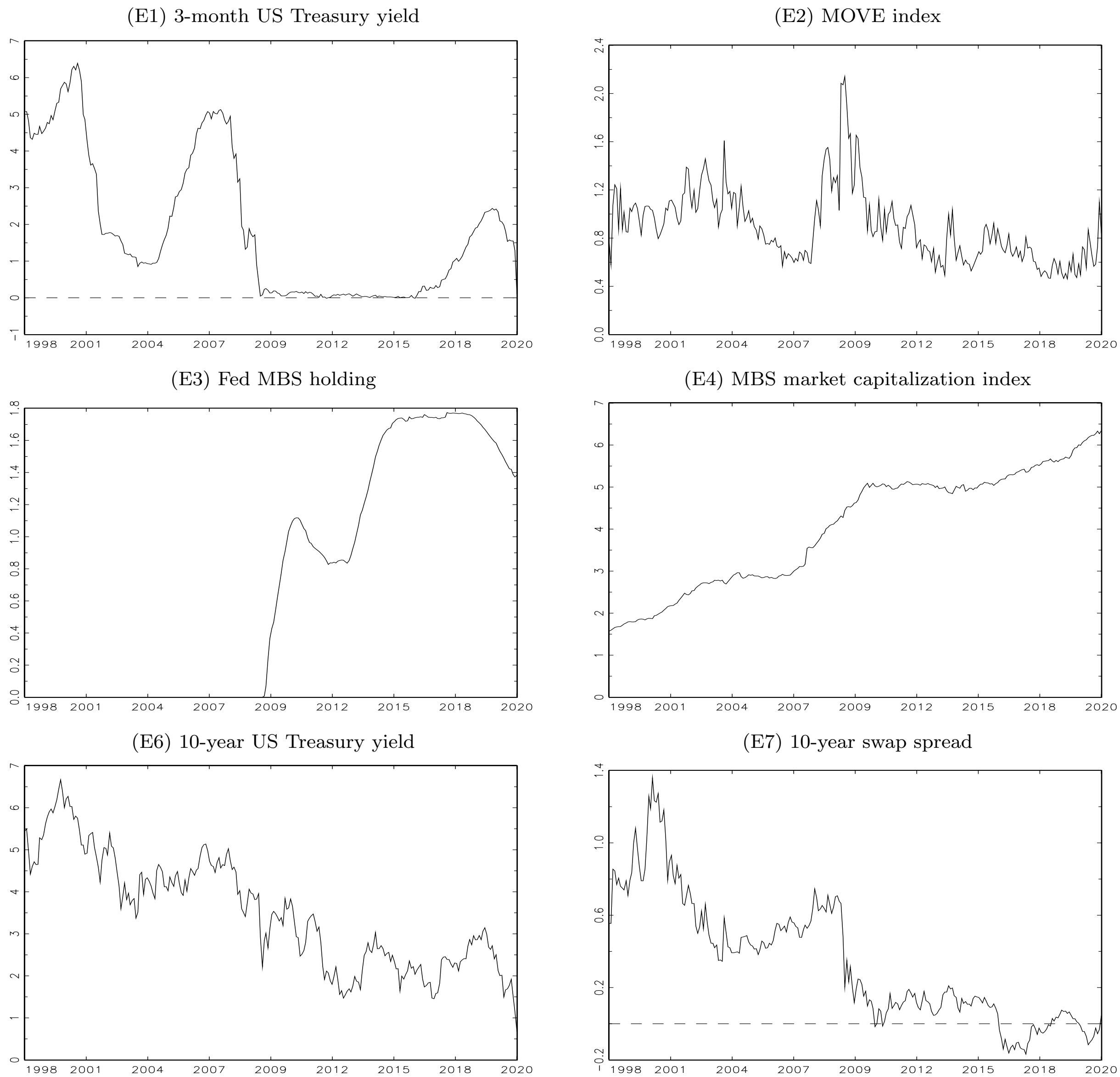

Figure 2. Explanatory variables for the period of June 1998 to March 2020.

Notes: (E6) 10-year US Treasury yield and (E7) 10-year swap spread are excluded from the econometric specification.

4.2. Model specification

For the t-QVARMA model, two alternative sets of dependent variables y_t are considered: First, (M1) Fannie Mae MBS spread, (M2) Freddie Mac MBS spread, and (M3) Ginnie Mae MBS spread. Second, (L1) Freddie Mac lending spread, (L2) fixed lending spread, and (L3) jumbo lending spread. Thus, $K = 3$ for both cases. The explanatory variables are: (E1) 3-month US Treasury yield, (E2) MOVE index, (E3) Fed MBS holding, (E4) MBS market capitalization index, and (E5) conservatorship dummy. Thus, $R = 5$ for the vector of the explanatory variables Z_t. The model is formulated as follows:

$$\begin{bmatrix} y_{1,t} \\ y_{2,t} \\ y_{3,t} \end{bmatrix} = \begin{bmatrix} \mu^*_{1,t} \\ \mu^*_{2,t} \\ \mu^*_{3,t} \end{bmatrix} + \begin{bmatrix} \mu^\dagger_{1,t} \\ \mu^\dagger_{2,t} \\ \mu^\dagger_{3,t} \end{bmatrix} + \begin{bmatrix} \mu^\circ_{1,t} \\ \mu^\circ_{2,t} \\ \mu^\circ_{3,t} \end{bmatrix} + \begin{bmatrix} v_{1,t} \\ v_{2,t} \\ v_{3,t} \end{bmatrix} \tag{16}$$

$$\begin{bmatrix} \mu^*_{1,t} \\ \mu^*_{2,t} \\ \mu^*_{3,t} \end{bmatrix} = \begin{bmatrix} \Phi^*_{1,1} & 0 & 0 \\ 0 & \Phi^*_{2,2} & 0 \\ 0 & 0 & \Phi^*_{3,3} \end{bmatrix} \begin{bmatrix} \mu^*_{1,t-1} \\ \mu^*_{2,t-1} \\ \mu^*_{3,t-1} \end{bmatrix} + \begin{bmatrix} \Psi^*_{1,1} & 0 & 0 \\ 0 & \Psi^*_{2,2} & 0 \\ 0 & 0 & \Psi^*_{3,3} \end{bmatrix} \begin{bmatrix} u_{1,t-1} \\ u_{2,t-1} \\ u_{3,t-1} \end{bmatrix} \tag{17}$$

$$\begin{bmatrix} \mu^\dagger_{1,t} \\ \mu^\dagger_{2,t} \\ \mu^\dagger_{3,t} \end{bmatrix} = \begin{bmatrix} \mu^\dagger_{1,t-1} \\ \mu^\dagger_{2,t-1} \\ \mu^\dagger_{3,t-1} \end{bmatrix} + \begin{bmatrix} \Psi^\dagger_{1,1} & \Psi^\dagger_{1,2} & \Psi^\dagger_{1,3} \\ \kappa_1\Psi^\dagger_{1,1} & \kappa_1\Psi^\dagger_{1,2} & \kappa_1\Psi^\dagger_{1,3} \\ \kappa_2\Psi^\dagger_{1,1} & \kappa_2\Psi^\dagger_{1,2} & \kappa_2\Psi^\dagger_{1,3} \end{bmatrix} \begin{bmatrix} u_{1,t-1} \\ u_{2,t-1} \\ u_{3,t-1} \end{bmatrix} \tag{18}$$

$$\begin{bmatrix} \mu^\circ_{1,t} \\ \mu^\circ_{2,t} \\ \mu^\circ_{3,t} \end{bmatrix} = \begin{bmatrix} \Psi^\circ_{1,1} & \Psi^\circ_{1,2} & \Psi^\circ_{1,3} & \Psi^\circ_{1,4} & \Psi^\circ_{1,5} \\ \Psi^\circ_{2,1} & \Psi^\circ_{2,2} & \Psi^\circ_{2,3} & \Psi^\circ_{2,4} & \Psi^\circ_{2,5} \\ \Psi^\circ_{3,1} & \Psi^\circ_{3,2} & \Psi^\circ_{3,3} & \Psi^\circ_{3,4} & \Psi^\circ_{3,5} \end{bmatrix} \times \begin{bmatrix} Z_{1,t} \\ Z_{2,t} \\ Z_{3,t} \\ Z_{4,t} \\ Z_{5,t} \end{bmatrix} \tag{19}$$

$$v_t \sim t_3 \left\{ \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \Omega^{-1}_{1,1} & 0 & 0 \\ \Omega^{-1}_{2,1} & \Omega^{-1}_{2,2} & 0 \\ \Omega^{-1}_{3,1} & \Omega^{-1}_{3,2} & \Omega^{-1}_{3,3} \end{bmatrix} \times \begin{bmatrix} \Omega^{-1}_{1,1} & \Omega^{-1}_{2,1} & \Omega^{-1}_{3,1} \\ 0 & \Omega^{-1}_{2,2} & \Omega^{-1}_{3,2} \\ 0 & 0 & \Omega^{-1}_{3,3} \end{bmatrix}, \nu \right\} \text{ i.i.d.} \tag{20}$$

The specification of $\Psi^\dagger$ ensures that the rank of the matrix is one (i.e. one common stochastic trend), which is motivated by the maximum eigenvalue tests of Johansen (1991). Variable μ_t^* is initialized by using a 3×1 vector of zeros. Variable $\mu_t^\dagger$ is initialized by using parameter vector $(\mu_0^\dagger, \kappa_1\mu_0^\dagger, \kappa_2\mu_0^\dagger)'$, which maintains the co-integration relation. The co-integration vector is $(1, -1/\kappa_1, -1/\kappa_2)'$. An alternative initialization for $\mu_t^\dagger$ is the use of the first observations of the dependent variables (Harvey 2013), for which we obtain results that are similar to those reported in this paper.

4.3. Empirical results

In the empirical analysis, more than 20 alternative specifications of the t-QVARMA model are estimated, for example, by considering diagonal or full matrices for Φ^* and Ψ^*, and by considering $\mu_t^* = 0_{3\times 1}$ or $\mu_t^\dagger = 0_{3\times 1}$ or $\mu_t^\circ = 0_{3\times 1}$. In this section, we present the best-performing alternatives for: (M1) Fannie Mae MBS spread, (M2) Freddie Mac MBS spread, and (M3) Ginnie Mae MBS spread; (L1) Freddie Mac lending spread, (L2) fixed lending spread, and (L3) jumbo lending spread.

Model selection is supported by the following statistics: (i) Akaike information criterion (AIC); Bayesian information criterion (BIC); Hannan–Quinn criterion (HQC). The use of these metrics for score-driven models is motivated in the work of Harvey (2013). (ii) Empirical estimates of the ML conditions C_1, C_2, C_3, and C_4. (iii) Ljung–Box (LB) test (Ljung and Box 1978) for the score functions $u_{1,t}$, $u_{2,t}$, and $u_{3,t}$. Testing the independence of the score functions is motivated by the works of Li (2004) and Harvey (2013), which provide robust residual diagnostics for the t-QVARMA model.

In Table 3, the parameter estimates and model diagnostics are presented for the best-performing t-QVARMA specification of dependent variables Fannie Mae MBS spread, Freddie Mac MBS spread, and Ginnie Mae MBS spread, for which Φ^* and Ψ^* are diagonal matrices. In Table 4, the parameter estimates and model diagnostics are presented for the best-performing t-QVARMA specification of dependent variables Freddie Mac lending spread, fixed lending spread, and jumbo lending spread, for which Φ^* and Ψ^* are diagonal matrices, and $\mu_t^\dagger = 0_{3\times 1}$. For both cases, the ML criteria and the LB test results support the use of the t-QVARMA model (Tables 3 and 4).

The use of μ_t^* is required in both cases due to the LB test results and according to the results, the diagonal matrix specifications of Φ^* and Ψ^* are the most appropriate to measure short-run dynamics. For MBS spreads, the best-performing specification includes μ_t^*, $\mu_t^\dagger$, and μ_t°. For the mortgage lending spreads, the best-performing specification includes μ_t^* and μ_t°, which shows that the co-integrating relationships for (L1) to (L3) are captured by the exogenous explanatory variables. The estimated time series components for the best-performing models are reported in Figures 3 and 4, respectively.

With respect to the significance of the parameters of the explanatory variables, robust results are estimated for MBS spreads and mortgage lending spreads (Tables 3 and 4).

First, the effects of the explanatory variables on MBS spreads are the following: For the 3-month US Treasury yield, significant positive effects are found for the Fannie Mae and Freddie Mac MBS spreads, and a non-significant effect is found for the Ginnie Mae MBS spread. The MOVE index has a significant positive effect on all MBS spreads. As nominal spreads contain refinancing option premium, it is intuitive to expect nominal spreads to widen when volatility is picking up. Fed MBS holding has a significant negative effect on all MBS spreads. According to the ML estimates, QE significantly lowered the Fannie Mae, Freddie Mac, and Ginnie Mae MBS spreads by 39.96, 35.90, and 45.76 basis points, respectively. This empirically confirms that QE contributed to narrower mortgage spreads. The MBS market capitalization index has a significant positive effect on all MBS spreads, showing that a growing MBS supply alone would have had a positive impact on mortgage spreads. Note, however, that GSE MBS market capitalization net of the Fed holding had in fact declined from 2009 until 2012, signifying the large scale of the Fed's intervention. The variable conservatorship dummy has a significant negative effect on all MBS spreads. According to the ML estimates, conservatorship significantly lowered the Fannie Mae, Freddie Mac, and Ginnie Mae MBS spreads by 31.91, 34.66, and 20.51 basis points, respectively. This is another important result, since it empirically confirms that placing the GSEs into conservatorship alone also contributed to lower GSE MBS spreads.

Second, the effects of the explanatory variables on mortgage lending spreads are the following: For the 3-month US Treasury yield, significant positive effects are found for Freddie Mac and fixed lending spreads, and a non-significant effect is found for jumbo lending spread. The MOVE index has significant positive effects on all mortgage lending spreads. The Fed MBS holding has significant negative effects on all mortgage lending spreads. According to the ML estimates, QE significantly lowered the Freddie Mac, fixed, and jumbo lending spreads by 71.91, 76.74, and 135.86 basis points, respectively. The MBS market capitalization index has significant positive effects on all mortgage lending spreads. The variable conservatorship dummy has significant negative effects on all mortgage lending spreads. According to the ML estimates, conservatorship significantly lowered the Freddie Mac, fixed, and jumbo lending spreads by 24.59, 35.40, and 26.23 basis points, respectively. These results empirically confirm that the policy actions of conservatorship and QE lowered mortgage lending spreads.

Table 3. ML estimates for Fannie Mae, Freddie Mac, and Ginnie Mae MBS spreads

Specification: Φ^* and Ψ^* are diagonal matrices							
$\Phi^*_{1,1}$	0.8425***(0.0267)	$\Psi^\circ_{1,1}$	0.0464**(0.0220)	$\Psi^\circ_{3,1}$	0.0221(0.0229)	LL	5.2359
$\Phi^*_{2,2}$	0.8289***(0.0293)	$\Psi^\circ_{1,2}$	0.3002***(0.0402)	$\Psi^\circ_{3,2}$	0.2661***(0.0366)	AIC	−10.2123
$\Phi^*_{3,3}$	0.8115***(0.0440)	$\Psi^\circ_{1,3}$	−0.3996***(0.0953)	$\Psi^\circ_{3,3}$	−0.4576***(0.1095)	BIC	−9.7492
$\Psi^*_{1,1}$	1.4897***(0.1370)	$\Psi^\circ_{1,4}$	0.2477***(0.0674)	$\Psi^\circ_{3,4}$	0.2015**(0.0937)	HQC	−10.0262
$\Psi^*_{2,2}$	1.4678***(0.1358)	$\Psi^\circ_{1,5}$	−0.3191***(0.1139)	$\Psi^\circ_{3,5}$	−0.2051**(0.1033)	C_1	0.8425
$\Psi^*_{3,3}$	1.2792***(0.1536)	$\Psi^\circ_{2,1}$	0.0480**(0.0206)	$\Omega^{-1}_{1,1}$	0.0809***(0.0046)	C_2	−0.1672
$\Psi^\dagger_{1,1}$	2.7638***(0.7654)	$\Psi^\circ_{2,2}$	0.3046***(0.0399)	$\Omega^{-1}_{2,1}$	0.0794***(0.0046)	C_3	0.8464
$\Psi^\dagger_{1,2}$	−3.0050***(0.8256)	$\Psi^\circ_{2,3}$	−0.3590***(0.0913)	$\Omega^{-1}_{2,2}$	0.0112***(0.0006)	C_4	0.7167
$\Psi^\dagger_{1,3}$	0.7063***(0.2336)	$\Psi^\circ_{2,4}$	0.2350***(0.0645)	$\Omega^{-1}_{3,1}$	0.0712***(0.0052)	LB $u_{1,t}$	10.5574(0.8359)
κ_1	0.9725***(0.0209)	$\Psi^\circ_{2,5}$	−0.3466***(0.1044)	$\Omega^{-1}_{3,2}$	0.0037(0.0026)	LB $u_{2,t}$	11.5528(0.7742)
κ_2	1.4383***(0.1426)			$\Omega^{-1}_{3,3}$	0.0361***(0.0020)	LB $u_{3,t}$	13.5060(0.6355)
$\mu^\dagger_0$	0.4163**(0.1797)			ν	3.4195***(0.3165)		

Notes: Maximum likelihood (ML); not available (NA); log-likelihood (LL); Akaike information criterion (AIC); Bayesian information criterion (BIC); Hannan–Quinn criterion (HQC); Ljung–Box (LB). Explanatory variables: (E1) 3-month US Treasury yield, (E2) MOVE index, (E3) Fed MBS holding, (E4) MBS market capitalization index, and (E5) conservatorship dummy. For the parameter estimates standard errors are reported in parentheses. For the LB test lag-order 16 is used which approximates $(T)^{1/2}$, and p-values are reported in parentheses. ** and *** indicate significance at the 5% and 1% levels, respectively.

Table 4. ML estimates for Freddie Mac, fixed, and jumbo lending spreads

Specification: Φ^* and Ψ^* are diagonal matrices; $\mu_t^\dagger = 0_{3\times 1}$							
$\Phi^*_{1,1}$	0.9663***(0.0132)	$\Psi^\circ_{2,1}$	0.0660***(0.0218)	$\Omega^{-1}_{1,1}$	−0.1262***(0.0064)	LL	2.4339
$\Phi^*_{2,2}$	0.9700***(0.0139)	$\Psi^\circ_{2,2}$	0.3552***(0.0660)	$\Omega^{-1}_{2,1}$	−0.1335***(0.0079)	AIC	−4.6541
$\Phi^*_{3,3}$	0.9549***(0.0129)	$\Psi^\circ_{2,3}$	−0.7674***(0.1946)	$\Omega^{-1}_{2,2}$	0.0728***(0.0039)	BIC	−4.2728
$\Psi^*_{1,1}$	1.1852***(0.1066)	$\Psi^\circ_{2,4}$	0.5193***(0.0546)	$\Omega^{-1}_{3,1}$	−0.1402***(0.0091)	HQC	−4.5009
$\Psi^*_{2,2}$	0.9804***(0.1019)	$\Psi^\circ_{2,5}$	−0.3540***(0.1223)	$\Omega^{-1}_{3,2}$	0.0108*(0.0055)	C_1	0.9700
$\Psi^*_{3,3}$	1.4690***(0.1236)	$\Psi^\circ_{3,1}$	0.0096(0.0243)	$\Omega^{-1}_{3,3}$	−0.0818***(0.0045)	C_2	−0.0305
$\Psi^\circ_{1,1}$	0.0465**(0.0200)	$\Psi^\circ_{3,2}$	0.3554***(0.0719)	ν	5.7813***(0.8579)	C_3	0.9700
$\Psi^\circ_{1,2}$	0.4034***(0.0561)	$\Psi^\circ_{3,3}$	−1.3586***(0.2479)			C_4	0.9408
$\Psi^\circ_{1,3}$	−0.7191***(0.2001)	$\Psi^\circ_{3,4}$	0.7393***(0.0675)			LB $u_{1,t}$	20.4263(0.2016)
$\Psi^\circ_{1,4}$	0.4853***(0.0570)	$\Psi^\circ_{3,5}$	−0.2623**(0.1206)			LB $u_{2,t}$	17.3529(0.3631)
$\Psi^\circ_{1,5}$	−0.2459**(0.1057)					LB $u_{3,t}$	21.5602(0.1580)

Notes: Maximum likelihood (ML); not available (NA); log-likelihood (LL); Akaike information criterion (AIC); Bayesian information criterion (BIC); Hannan–Quinn criterion (HQC); Ljung–Box (LB). Explanatory variables: (E1) 3-month US Treasury yield, (E2) MOVE index, (E3) Fed MBS holding, (E4) MBS market capitalization index, and (E5) conservatorship dummy. For the parameter estimates standard errors are reported in parentheses. For the LB test lag-order 16 is used which approximates $(T)^{1/2}$, and p-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

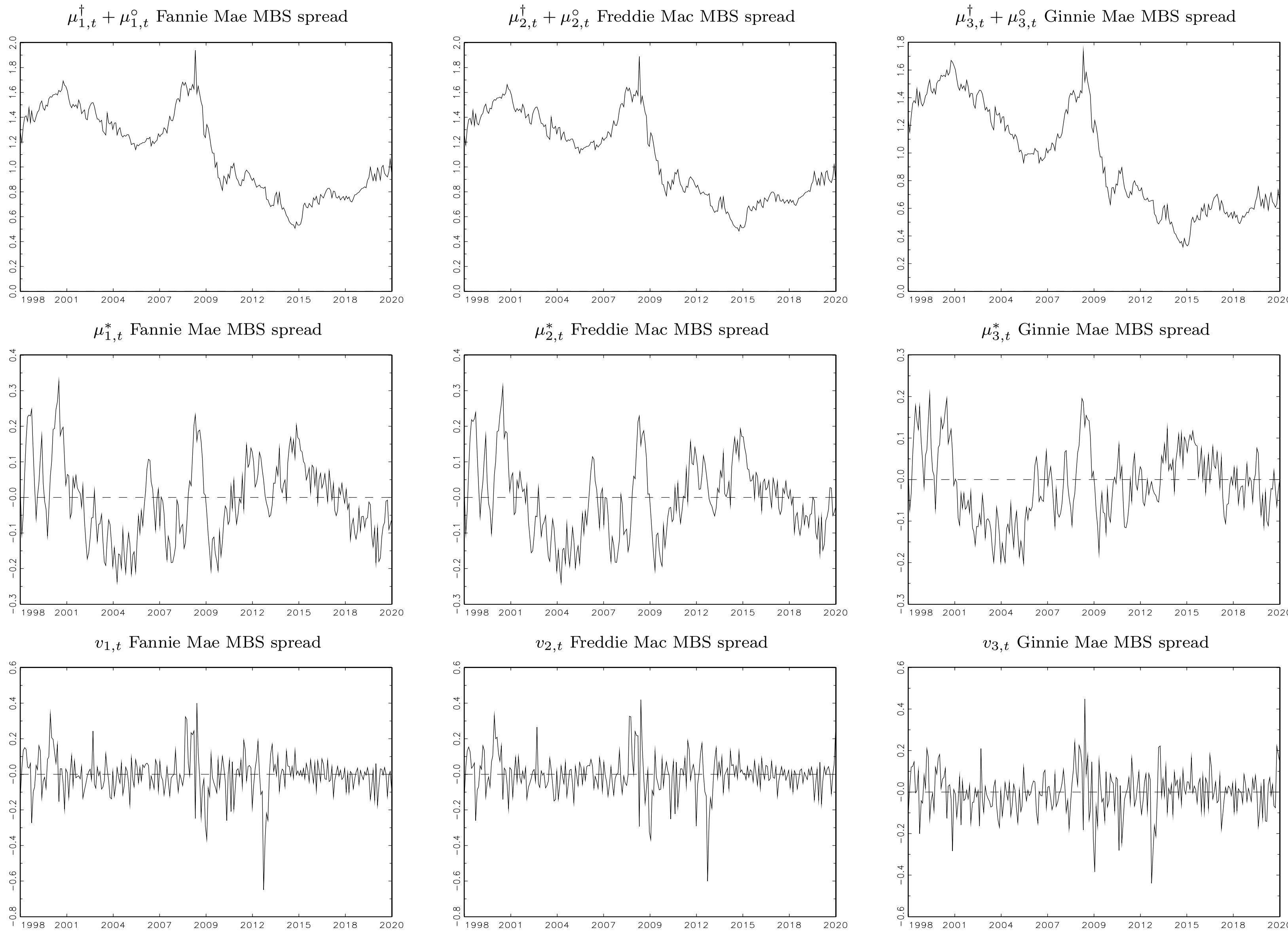

Figure 3. Time series components $\mu^{\dagger}_t + \mu^{\circ}_t$, μ^{*}_t, and v_t for (M1) Fannie Mae MBS spread, (M2) Freddie Mac MBS spread, and (M3) Ginnie Mae MBS spread.
Notes: Φ^{*} and Ψ^{*} are diagonal matrices (Table 3).

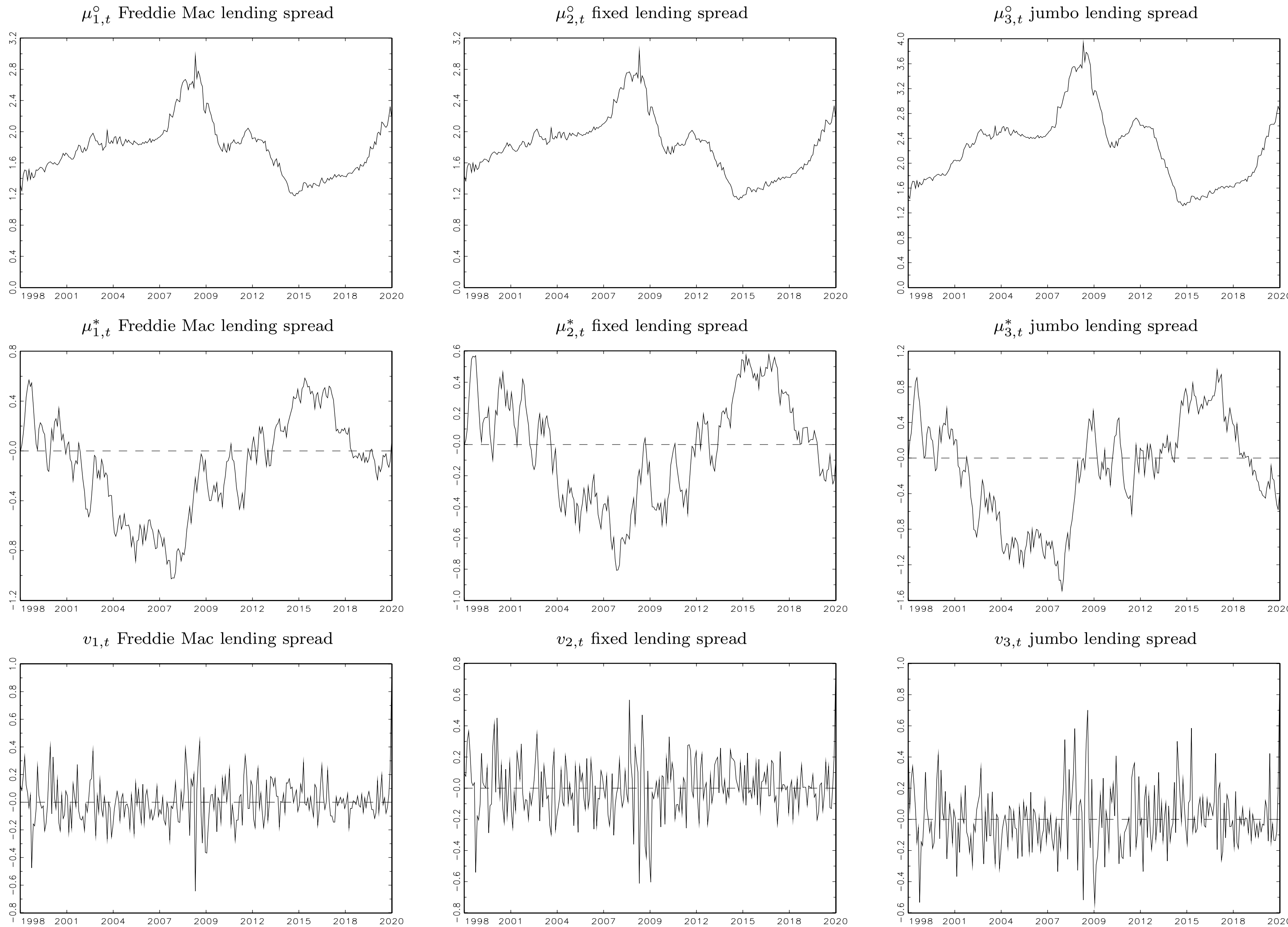

Figure 4. Time series components μ_t°, μ_t^{*}, and v_t for (L1) Freddie Mac lending spread, (L2) fixed lending spread, and (L3) jumbo lending spread.
Notes: Φ^* and Ψ^* are diagonal matrices; $\mu_t^{\dagger} = 0_{3\times 1}$ (Table 4).

5. Conclusions

The perception of government backing (a.k.a. implicit guarantee) was an ambiguity created by the US Government. That ambiguity fostered an enormous growth in outstanding GSE debt, which created a significant instability to the US financial system and beyond. To manage that instability, the US Government placed the GSEs into conservatorship and engaged in extensive QE programs. In this paper, we have investigated the effect of those policies on MBS investors and mortgage borrowers. We have suggested the use of a multi-equation score-driven model, to improve the measurements of the specific effects of two policy actions for the period of the unconventional monetary policy: (i) placement of Fannie Mae and Freddie Mac into US Government conservatorship, and (ii) the Fed's QE programs which involved large-scale US Treasury bond purchases, and LSAPs from GSEs.

The measurement of the former policy action contributes to the literature, because, to the best of our knowledge, the effects of conservatorship on MBS and mortgage lending spreads have not been measured in the literature to date. The sample sizes of relevant works of the literature have been extended, to improve the estimates of policy effects. For the period of June 1998 to March 2020, monthly data have been used for: (i) Fannie Mae, Freddie Mac, and Ginnie Mae MBS spreads, (ii) Freddie Mac, fixed, and jumbo mortgage lending spreads, and (iii) explanatory variables that approximate policy actions and control for relevant economic conditions for the US mortgage lending market.

The score-driven model of this paper is able to capture general time series dynamics of the dependent variables, by using $I(0)$ and co-integrated $I(1)$ components, and by using information-theoretic optimal updating mechanisms. Several alternative specifications of the multi-equation score-driven model have been compared by using likelihood-based metrics, empirical estimates of ML conditions, and robust residual diagnostics. The exogeneity assumption of the explanatory variables has been supported by the general time series dynamics of the dependent variables, the robust residual tests, and the careful choice of the explanatory variables included in the reported specifications.

For the best-performing specifications of the score-driven model, we have obtained robust negative effects of both policy actions on all GSE MBS spreads and on all mortgage lending spreads. Our results provide a robust empirical contribution to the literature, in which mixed findings are reported about the effects of the Fed's unconventional monetary policy on treasury bond yields, GSE MBS current coupon rates, mortgage lending rates, and the corresponding mortgage spreads in the US.

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