Financial Stress and Equilibrium Dynamics in Term Interbank Funding Markets*

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Abstract

Interbank funding markets are central to the functioning of the financial system and the transmission of monetary policy. Libor-OIS spreads have been widely-used indicators of conditions in these markets. We construct models that incorporate the long-run equilibrium relationship between term Libor and OIS rates and their regime-dependent dynamics. We find strong evidence for three regimes in the interbank funding market that resemble different pricing of risk and equilibrium outcomes, as suggested by the recent theoretical literature. We show that significant adjustments toward long-run equilibrium typically occur following large shocks to risk premia, but this relationship tends to breakdown in moderate stress regimes. We provide point and interval estimates for stress thresholds that serve as potential benchmarks for policy makers and market participants to assess funding conditions.

Keywords: Interbank markets, Libor-OIS spread, credit risk, liquidity risk, cointegration, threshold models, GARCH, DCC

JEL Classification: C32, E44, E52, G01, G21

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1 Introduction

Interbank funding markets play a crucial role for the functioning of the financial system and the transmission of monetary policy. Strains in these markets may impair the flow of credit to the entire economy (see for example, Ivashina et al. (2015)). Until the global financial crisis of 2007-2009, interbank funding markets had been highly liquid and generally stable. However, conditions in these markets changed abruptly at the onset of the crisis. Following the announcement by BNP Paribas on August 9, 2007 to suspend withdrawals from some of its investment funds exposed to U.S. subprime mortgage backed assets, interbank funding markets displayed signs of stress. Discrete repricing of credit and liquidity risks led to large jumps in key risk spreads, especially those associated with term interbank lending. Stress in short-term funding markets and the broader financial system persisted and reached extremely elevated levels in the Fall of 2008 following the bankruptcy of Lehman Brothers. Reversal to a state of normal functioning in interbank markets took place amid bank recapitalizations, extension of government guarantees on bank liabilities, and unprecedented levels of liquidity provision by the Federal Reserve (Fed).

In this paper, we analyze the behavior of interbank interest rates using nonlinear models that characterize their long-run equilibrium relationship and state-dependent dynamics. We focus on the term Libor and overnight index swap (OIS) rates and their spreads, which are widely-used indicators of conditions in funding markets.[1] Libor-OIS spreads are monitored by both market participants and policy makers to gauge the pricing of risk and the health of the banking system.[2] The building block of our empirical framework is the long-run equilibrium relationship between Libor and OIS rates that emerge from dynamic repricing of risk and policy intervention during times of stress. Hence, the spreads between these rates reflect mean-reverting, albeit persistent, composite risk premia. We incorporate this idea into bivariate dynamic models for the two rates, in which the Libor-OIS spread serves as an error correction term to quantify deviations of the rates from their long-run equilibrium. Our models feature multiple regimes determined by the level of risk premia reflecting different equilibrium outcomes. These outcomes are associated with

[1] We provide detailed background information on these rates and the related literature in Section 2.

[2] For example, the Fed staff indicated in the Greenbook dated October 2008 that "...In short-term funding markets, spreads between term Libor and overnight index swap (OIS) rates soared to record highs, ..." (available at https://www.federalreserve.gov/monetarypolicy/files/FOMC20081029gbpt120081022.pdf) Former Fed chairman Alan Greenspan stated in an interview in early 2009 that "Libor-OIS remains a barometer of fears of bank insolvency" (see Thornton (2009)).

changing fundamentals and risk appetite, as well as increased likelihood of policy intervention during times of stress.

Our empirical setup has solid theoretical foundations. Freixas and Jorge (2008) build a partial equilibrium model of the interbank market that features asymmetric information and emphasize distinct *regimes* with respect to aggregate liquidity. Acharya et al. (2012) argue that even states of aggregate liquidity surplus can effectively feature liquidity shortage due to market power of some banks. Acharya and Skeie (2011) show that during times of elevated rollover risk—the risk that a bank will not be able to refinance its debt before the loan it provides in the interbank market matures—banks hoard liquidity, resulting in a decline in interbank lending and a rise in risk premiums. Heider et al. (2015) develop a model of interbank markets with endogenous liquidity and counterparty risk that stems from asymmetric information. Their model admits three outcomes: a full participation equilibrium with subdued interest rates, an adverse selection equilibrium with a higher interest rate, and a market freeze with no trading. The transition across these outcomes take place amid changes in quality and quantity of risky assets in the banking system.[3]

Both the aforementioned developments during the financial crisis and the theoretical literature suggest that an empirical model of interbank rates should incorporate dynamic repricing of risk and state-dependent equilibrium outcomes. We indeed find strong evidence of state-dependent dynamics in the interbank funding market. We document asymmetry in the long-run equilibrium relationship between the Libor and OIS rates at different maturities. Three regimes adequately capture the overall behavior of the system: a state of normal functioning, and states of moderate- and high-stress. We quantify funding pressure points for each considered maturity by providing point and interval estimates for the spread thresholds that identify these regimes. Our threshold estimates serve as potential reference points for both policy makers and market participants to evaluate any buildup of stress due to higher liquidity or credit risk in these markets in a historical context. In addition, we quantify abrupt shifts in volatilities of interest rates associated with elevated stress, and show that their correlations decline considerably in such regimes.

[3]In related literature that focus on broader financial markets and their interaction with the real economy, Brunnermeier and Sannikov (2014) build a model with financial frictions in which nonlinear amplification effects result in episodes of high volatility. He and Krishnamurthy (2012) also develop a general equilibrium model in which capital shocks reduce financial intermediaries risk bearing capacity, leading to a state of higher risk premia and elevated volatility of risky asset prices.

Our three-regime model successfully characterizes different phases of the interbank funding markets during the global financial crisis. In the aftermath of the crisis, the model identifies two episodes of moderate stress, driven by different components of risk contained in the Libor-OIS spread. First, in mid-2011, the spread exceeded the low threshold estimate as the European sovereign debt crisis intensified and credit risk perception in interbank markets shifted. More recently, there has been an increase in the Libor-OIS spreads leading up to the compliance date of the money fund reform in October 2016. Money funds' reduced appetite for term lending likely pushed liquidity premiums up and led to higher Libor-OIS spreads. This is marked by a switch from to the moderate-stress regime in August 2016 in our model. As the banking system adjusted to the new reality, the system reverted back to the normal regime at the end of October. According to a more conservative estimate based on the interval estimates, this adjustment took a few months longer. Around the time when the Libor-OIS spread started to widen due to term funding pressures in response to the rule changes, it was not clear whether this would imply a permanent change in the pricing of term funding. An important takeaway from our results for this recent episode is that, rather than a permanent structural break, the elevated spread most likely reflected a transitory switch to a moderate-stress regime.

We also document pronounced asymmetries in the equilibrium adjustment mechanism, which are masked in a conventional linear model. We find that economically and statistically significant adjustments toward long-run equilibrium occur following sizable shocks to risk premia. The adjustments in the high-spread regime likely reflect a combination of factors such as balance sheet adjustment by banks as well as policy intervention to reduce liquidity and credit risk premia. When spreads are subdued, the tendency of the system to move toward long-run equilibrium is relatively sluggish. On the other hand, the intermediate regime is associated with large and persistent fluctuations in the spread and lack of adjustment of the rates toward their long-run equilibrium.

Our results are robust to potential structural instabilities as well as possible misrepresentation of reported interbank rates. When we re-estimate the models using data only since August 2007, we obtain qualitatively similar results. In addition, we use two alternative measures obtained from forward rate agreements (FRA) and interest rate swaps (IRS) that are free from issues that may have contaminated reported Libor figures. The FRA-OIS and IRS-OIS spreads reflect market participants' short- and medium-term expectations of the Libor-OIS spread under risk-neutrality, respectively. We document similar asymmetries for these measures as well, and obtain their respective point and interval stress thresholds estimates.

Our paper is related to three important strands of the empirical literature. First, a growing literature, attempts to measure the level of stress in financial markets by combining information from various indicators, see for example, Carlson et al. (2011), Hakkio and Keeton (2009), and Oet et al. (2011) among others. In this vein, Carpenter et al. (2014) extract a common component from various spreads to measure stress in money markets. In contrast, we estimate stress thresholds for Libor-OIS spreads, which are commonly monitored indicators of functioning and funding pressures in interbank markets. Second, some studies, such as Taylor and Williams (2009) and McAndrews et al. (2015), investigated whether the credit or liquidity risk component of Libor-OIS spreads played a bigger role during the global financial crisis. We focus on the Libor-OIS as a composite risk premium and incorporate the potentially state-dependent role of different components in a long-run equilibrium framework. Finally, several papers adopt the threshold error correction framework to study the relationship between financial asset prices, see for example, Dwyer et al. (1996), Martens et al. (1998), and Theissen (2012) who estimate models of nonlinear price discovery motivated by arbitrage arguments. Anderson (1997) and Seo (2003) analyze dynamics of default-free Treasury yields in the context of threshold error correction models based on similar arguments.

The remainder of the paper proceeds as follows: Section 2 provides background information on interbank markets, discusses the related literature, and describes the data. Section 3 lays out the econometric framework. Section 4 presents and discusses the empirical results. Section 5 concludes.

2 Interbank Funding Markets: Background and Data

2.1 The Libor-OIS Spread

The primary indicator of borrowing costs for interbank transactions has been the London interbank offered rate (Libor) over the past three decades. Libor represents the average interest rate at which large banks with London offices could borrow funds in a given currency for a certain period.[4] Historically, Libor has been a *reported* rate, which is supposed to reflect actual borrowing costs but not necessarily based on actual transactions data. Allegations of possible misrepresentation of Libor by certain banks emerged in 2008 (see Mollenkamp and Whitehouse (2008)). Formal investigations revealed manipulation of the rates with the intent of projecting financial soundness as well as benefiting trading positions. According to Hou and Skeie (2014), four major banks paid fines exceeding USD 3.5 billion in relation to such allegations in successive settlements in 2012 and 2013. Against this backdrop, a review of the Libor mechanism was initiated in 2012 and resulted in a report that set out a ten-point plan for reform (see Wheatley (2012)). Among the suggestions of the report was transferring responsibility to administer LIBOR from the British Bankers Association to a new administrator. Intercontinental Exchange Inc. (ICE) formally took over in February 2014. ICE is currently implementing further reforms toward basing Libor on transactions data to the greatest extent possible (see ICE (2016)).

Although the legal proceedings indicate that there had been manipulation of Libor, research based on available data do not provide conclusive evidence in terms of the magnitude of such effects. Abrantes-Metz et al. (2012) build on Mollenkamp and Whitehouse (2008) and conclude that the evidence is not consistent with a material manipulation of the 1-month Libor. Kuo et al. (2012) compare Libor survey responses to two novel measures of bank funding rates obtained from transaction data and conclude that Libor broadly tracks the alternative measures between 2007-2009, although it was below them at certain times, particularly at the height of the crisis. They also discuss a range of factors other than manipulation that are consistent with the presence of this gap. In contrast, Snider and Youle (2014) find evidence consistent with manipulation driven by trading positions, and Youle (2014) estimates that the average bias is about eight basis points for the 3-month term.

As discussed in McAndrews et al. (2015) a term interbank rate consists of four main components: (i) expected average of the corresponding overnight interest rate, (ii) the term premium, (iii) the credit risk premium, and (iv) the funding liquidity risk premium. The term premium reflects uncertainty about the path of expected overnight funding rates. The credit risk premium is compensation for risk of default. The funding liquidity premium is a function of the asset

[4] Because we exclusively focus on the term U.S. dollar interbank funding markets, we will refer to USD Libor simply as Libor.

liquidity of banks, their funding structure, and the expected liquidity conditions. A commonly monitored risk measure subtracts the respective overnight index swap (OIS) rate from Libor. In an OIS, a fixed rate is swapped for the geometric average effective federal funds rate over the contract period. Because OIS contracts are subject to collateralization and only net cash flows are exchanged at maturity, there is minimal counterparty credit risk in such transactions.[5] Therefore, the OIS rates are composed of the first two components described above, and the Libor-OIS spreads mainly reflect credit and funding liquidity risk premia.[6]

Recent literature produced mixed evidence regarding the relative importance of credit and funding liquidity risk premia in driving the Libor-OIS spreads. Taylor and Williams (2009) argue that increasing Libor-OIS spreads during the early stages of the financial crisis mainly reflected larger credit risk premia—as measured in the form of credit default swap (CDS) premiums—and were little affected by liquidity injections by the Fed. In contrast, McAndrews et al. (2015) claim that the Taylor-Williams results are subject to econometric biases, and conclude that term lending by the Fed actually resulted in lower Libor-OIS spreads by reducing the liquidity risk premia. Gefang et al. (2011) estimate a dynamic model with latent factors representing credit and liquidity risk based on bank-level Libor and CDS data, and attribute a greater role to the liquidity risk in driving the Libor-OIS spread higher during the 2007–2009 financial crisis. King and Lewis (2015) estimate a model that incorporates potential misreporting using matched bank-level Libor and CDS data. They conclude that although credit risk may have dominated at the height of the crisis, liquidity risk plays a greater role in driving the Libor-OIS spread.[7]

All told, available evidence suggest that *both* credit and liquidity risk play an important role in the dynamics of Libor-OIS spreads, with their relative importance potentially changing depending on the prevailing market conditions. Our approach incorporates these aspects by

[5] Because the underlying rate for OIS contracts is the unsecured federal funds rate, the OIS rates are in principle reflective of average credit risk in the overnight interbank lending transactions. However, Afonso et al. (2011) find that increased default risk is usually associated with credit rationing instead of higher risk premiums in the federal funds market.

[6] Michaud and Upper (2008) suggest that market liquidity and microstructure effects may also affect Libor-OIS spreads.

[7] Christensen et al. (2014) analyze spreads of Libor over comparable maturity Treasury yields in the context of an arbitrage-free term structure model and find that the Fed liquidity facilities resulted in lower liquidity premiums and helped to bring down the spreads. Angelini et al. (2011) focus on the spreads between euro-area term interbank rates relative to repo rates and identify credit risk as their main driver after August 2007. Schwarz (2016) also studies euro-area data and finds a dominant role for liquidity risk in driving interbank risk spreads.

treating the Libor-OIS spread as a composite risk premium with potentially changing role of different components depending on the state of the markets.

2.2 Data and Descriptive Statistics

We focus on the 1-, 3-, and 6-month tenors as these are the most commonly monitored and referenced rates. Moreover, Duffie et al. (2013) estimate that bulk of the term interbank lending activity takes place at these maturities. The 3-month tenor is especially important as it forms the reference rate for most USD-denominated interest rate swaps and other interest rate derivatives. Our data set consists of weekly observations from January 1, 2002 to March 22, 2017, where availability of the OIS data determines the beginning of our sample period. Weekly series are constructed as averages of daily series as of each Wednesday. We obtain both Libor and OIS data from Bloomberg. These interest rates are plotted in Figures 1 and 2.

Table 1 reports descriptive statistics for the spreads in the subsamples (panels a-c), as well as the full sample (panel d). Overall, the level, volatility, and persistence of the spreads have been an increasing function of maturity both in the subsamples and over the entire period. The Libor-OIS spreads had been fairly tight prior to mid-2007, with averages close to 10 basis points across the three tenors (panel a). The difference between 1-month and 6-month spreads was around 3 basis points on average. Following the suspension of withdrawals by BNP Paribas from some of its investment funds exposed to the U.S. subprime mortgage backed assets on August 9, 2007, risk perceptions shifted and spreads at all maturities increased markedly, as can be seen from Figure 3. This development was perceived to be an important sign of the propagation of stress related to mortgage backed securities in the broader financial system, and marked the beginning of the financial crisis. During the following two years, the *average* Libor-OIS spreads ranged from 56 to 108 basis points (panel b). In October 2008, following the Lehman Brothers bankruptcy, spreads exceeded 300 basis points at all tenors. Since mid-2009, the end of the Great Recession according to the NBER, the spreads have been fluctuating around 9, 20, and 38 basis points for 1-, 3- and 6-month tenors, respectively (panel c).

3 Methodology

For a given spread, dynamics of the underlying pair of interest rates can be captured by a vector error-correction (VEC) model where the spread serves as the error correction term. This argument is based on the observation that the two time series can both be approximated as integrated processes, and they are not expected to drift away from each other for a prolonged time due to mean reversion in risk premia.[8] Let y_t denote a 2×1 vector of interest rates underlying a given spread. The linear VEC model with p lags is given by,

$$\Delta y_t = \Psi X_t + \epsilon_t, \tag{1}$$

where $\Psi = (c, \phi, A_1, \ldots, A_p)$, $X_t = (1, s_{t-1}, \Delta y'_{t-1}, \ldots, \Delta y'_{t-p})'$, and $s_t = y_{2,t} - y_{1,t}$. The innovation vector, ϵ_t, is assumed to be martingale difference with time-varying heteroskedasticity with elements that are allowed to be contemporaneously correlated.

The linear VEC specification has important limitations. The model implicitly assumes that deviations of the spread from its long-run equilibrium decrease at a pace that is independent of the level of the spread. However, the interbank funding market is more likely to be characterized as a dynamic system with different states each with distinct features driven by banks' adjustments to their asset and liability structures, changes in risk appetite, as well as policy intervention. Indeed, Heider et al. (2015) develop a model of interbank funding market with endogenous liquidity and asymmetric information that can potentially generate markedly different outcomes. Specifically, their model admits a full-participation equilibrium with a low interest rate, an adverse selection equilibrium with a higher interest rate, and a complete market breakdown. Similarly, in Acharya and Skeie (2011)'s model of the interbank market, increases in illiquidity of bank assets and short-term leverage can lead to substantially lower equilibrium lending and higher interest rates. A nonlinear VEC model can adequately reflect such distinct states of the interbank funding market. Therefore, we allow for regime-switching in the parameters of the VEC model to characterize potential discontinuous adjustment to equilibrium as well as other asymmetries. We assume that the level of the lagged spread between the two rates, which serves as the error correction term, determines the regimes associated with different dynamics.

[8] See 4.1 for unit root and cointegration tests.

The n-state threshold VEC (TVEC) model in this context can be written as follows:

$$\Delta y_t = \sum_{j=1}^{n} \Psi^j X_t \mathbf{1}(\gamma_{j-1} < s_{t-1} \leq \gamma_j) + \epsilon_t, \tag{2}$$

where $\Psi^j = \left(c_j, \phi_j, A_1^j, \ldots, A_p^j\right)$. The parameters $\{\gamma_j\}_{j=0}^n$ are the threshold values such that $\gamma_0 = -\infty$ and $\gamma_s = \infty$, and $\mathbf{1}(\cdot)$ is the standard indicator function. The model assumes that there are n different regimes in which Δy_t follows a linear process, but the general dynamics of Δy_t over time are described by a nonlinear process. When $n = 1$, the threshold model boils down to the linear model in equation 1.

We test for the threshold effects in the VEC model by considering the null hypothesis that Δy_t is linear (equation 1) against the alternative hypothesis that it follows a nonlinear process as in equation 2. The presence of nuisance parameters that are undefined under the null hypothesis of linearity complicate the otherwise standard procedures of Wald or likelihood ratio testing (see for example Davies (1977)). We follow the recursive residual-based testing method of Tsay (1998) that yields easy to compute test statistics with standard asymptotic distributions.

We estimate the threshold model using conditional least squares (CLS). Without loss of generality, let us illustrate the estimation procedure for the two-state case, i.e., $n = 2$, where the model is given by,

$$\Delta y_t = \Psi^1 X_t \mathbf{1}(s_{t-1} \leq \gamma_1) + \Psi^2 X_t \mathbf{1}(s_{t-1} > \gamma_1) + \epsilon_t.$$

Let $\widetilde{X}_t = \left(X_t' \mathbf{1}(s_{t-1} \leq \gamma_1), X_t' \mathbf{1}(s_{t-1} > \gamma_1)\right)'$ and $\Theta = \left(\Psi^1, \Psi^2\right)$, then the model can be compactly written as $\Delta y_t = \Theta \widetilde{X}_t + \epsilon_t$. For a given value of the threshold, γ_1, the CLS estimate of Θ is defined as follows,

$$\widehat{\Theta}'(\gamma_1) = \left[\sum_t \widetilde{X}_t \widetilde{X}_t'\right]^{-1} \left[\sum_t \widetilde{X}_t y_t'\right].$$

Let $\widehat{\epsilon}_t = y_t - \widehat{\Theta}(\gamma_1)\widetilde{X}_t$, then the total sum of squares (SSR) as a function of the threshold is given by $SSR(\gamma_1) = \operatorname{tr}\left(\sum_t \widehat{\epsilon}_t \widehat{\epsilon}_t'\right)$ where tr(.) denotes the trace operator. Finally, the CLS estimate of γ_1 is obtained from

$$\widehat{\gamma}_1 = \underset{\gamma_1}{\operatorname{argmin}}\, SSR(\gamma_1),$$

where $\gamma_1 \in \mathbb{R}_0$, $\mathbb{R}_0 \subset \mathbb{R}$, i.e. $\mathbb{R}_0$ is a bounded subset of the real line. In practice, we use a symmetrically trimmed version of the set $S = \{s_1, \ldots, s_{T-1}\}$, and consider trimming percentages of 15, 10, and 5%. The resulting least squares estimate of Θ is $\widehat{\Theta}(\widehat{\gamma}_1)$. In case of the three-regime model, we estimate the first threshold with 15% trimming and then conduct another grid search for the second threshold in a similar fashion with 5% trimming.

Inference on the parameters of the TVEC model is conducted via asymptotic methods and subsampling. Because the threshold estimate converges at rate T, we treat the threshold as known to conduct inference on Θ that converge at rate of $\sqrt{T}$. However, the distribution of the threshold estimate is not asymptotically nuisance-parameter-free, so we use the subsampling methods proposed by Politis et al. (1999) to construct asymptotically valid confidence intervals for the threshold parameter(s).[9]. Let b denote the block size such that $1 < b < T$; we estimate the model on blocks $\{y_t, \ldots, y_{t+b-1}\}_{t=1}^{T-b+1}$. Assuming that $b \to \infty$ and $b/T \to 0$, the confidence interval based on estimates from the blocks has the desired coverage probability. To satisfy this requirement we set $b = \lceil 3T^{1/2} \rceil$ where $\lceil . \rceil$ is the ceiling function.

We estimate a multivariate GARCH model for the innovations from the TVEC model to capture substantial volatility clustering in the data. We assume that volatility of the innovations are fully time-varying, but their correlations are constant in each state after we account for heteroskedasticity. Therefore, our approach can be regarded as a hybrid of the constant conditional correlation model of Bollerslev (1990) and the dynamic conditional correlation model of Engle (2002).[10] Specifically, let $H_t = \text{Cov}(\epsilon_t | \Omega_{t-1})$, then we can write

$$H_t = D_t R_t D_t,$$

where $D_t = diag\left\{\sqrt{\text{Var}(\epsilon_{it}|\Omega_{t-1})}\right\}$ for $i = 1, 2$, Ω_t denotes time t information, and $R_t = Corr(\epsilon_t|\Omega_{t-1})$. We consider the following threshold GARCH (1,1) specification for the elements of D_t:

$$d_{it}^2 = \mathbf{1}(\gamma_{j-1} < s_{t-1} \leq \gamma_j)\omega_{i,j} + \alpha_i \epsilon_{i,t-1}^2 + \beta_i d_{i,t-1}^2 \tag{3}$$

[9] See for example Gonzalo and Wolf (2005) for a similar application of subsampling in the case of univariate threshold autoregressive models

[10] Models that allow for time-varying correlations within each state are not supported by the data in any of the cases we analyze.

where $\omega_{i,j} = (1-\alpha_i-\beta_i)\sigma^2_{i,j}$ and $\sigma^2_{i,j} = E\left[\epsilon^2_{it} \mid \gamma_{j-1} < s_{t-1} \leq \gamma_j\right]$. Then the conditional correlation at any point in time is simply the correlation coefficient of the resulting GARCH residuals in the corresponding regime. Formally, let $e_{it} = \epsilon_{it}/d_{it}$ and $\rho_j = E\left[e_{1,t}e_{2,t} \mid \gamma_{j-1} < s_{t-1} \leq \gamma_j\right]$, then the off-diagonal element of the conditional correlation matrix R_t, say ρ_t, is given by $\rho_t = \mathbf{1}(\gamma_{j-1} < s_{t-1} \leq \gamma_j)\rho_j$.

To cross-check the TVEC model estimates and further explore dynamics of the spreads, we also estimate univariate threshold models for each of the spreads. The first-order self-exciting threshold autoregression (SETAR) model for the spreads is given by:

$$s_t = \sum_{j=1}^{n} \delta^j z_t \mathbf{1}(\gamma_{j-1} < s_{t-1} \leq \gamma_j) + \zeta_t,$$

where $z_t = (1, s_{t-1})'$, $\delta^j = (\mu_j, \kappa_j)$, and ζ_t is martingale difference with time-varying heteroskedasticity, which is modeled via the threshold GARCH specification given in equation 3.

4 Empirical Results

4.1 Testing for Unit Root, Cointegration and Nonlinearity

Following Balke and Fomby (1997) we implement a two-step procedure for testing. We first test for cointegration between Libor and OIS rates, and then explore potential nonlinearities in their long-run relationship. Table 2 summarizes the results of the unit root tests for the interest rates and spreads under consideration. We report the test statistics proposed by Elliott et al. (1996) and Ng and Perron (2001) as they are shown to have higher power against persistent alternatives. Both types of test statistics suggest that interest rates are well approximated by an integrated process over the full sample as we cannot reject the null of a unit root at conventional levels (panel a). The potential cointegrating relationship we focus on crucially depends on whether the spread between the two interest rate series is integrated in each case. Therefore, tests of cointegration boil down to tests of unit root for the spreads in this framework. Test statistics shown in panel b reject the null of unit root for spreads and confirm that each pair is cointegrated over the full-sample period. This result lays the foundation of our modeling strategy where the spreads between the two rates serve as error correction terms in the VEC models. The economic rationale for this relationship is the dynamic repricing of risk driven by changing fundamentals and risk appetite, as well as policy intervention during times of stress.

Table 3 summarizes the results of Tsay (1998)'s threshold nonlinearity test for the null of a first-order linear VEC against the corresponding TVEC where the spread serves as both the error correction term and the variable determining the regimes.[11] The initial sample size used to start the recursion is $T_0 = \lceil cT^{1/2} \rceil$ where $c \in \{2, \ldots, 5\}$. The null of linearity is strongly rejected for 3- and 6-month tenors regardless of the value of T_0, while significance is somewhat weaker in case of the 1-month tenor. Overall, evidence for non-linear dynamics in the Libor-OIS relationship is strong.

Because the threshold nonlinearity test is not informative about the number of regimes, we mainly rely on information criteria. Specifically, we base our selection on the Hannan-Quinn criterion following Guidolin and Timmermann (2006).[12] Given the available sample size and our interest in allowing for the possibility of three distinct regimes motivated by anecdotal evidence and theoretical models, we restrict our attention to the case of the first order model, i.e. $p = 1$. Table 4 summarizes the results. Threshold models are strongly favored over linear models, and the three-regime model over the two-regime model for all tenors. In addition, plots of SSR as a function of the threshold (not shown) also indicate that the three-regime model is the preferred model. In what follows, we focus on the first-order TVEC models with three regimes.

4.2 Threshold Estimates and Regimes

The threshold estimates and their subsampling-based confidence intervals at the 90% confidence level are shown in Table 5. Regime classifications from the TVEC models are plotted in Figures 4 to 6. In these figures, panels a, b and c show the regime classification based on the lower bound of the confidence interval for the threshold, its point estimate, and the upper bound of its confidence interval, respectively. Unless otherwise noted, we will refer to regime-classifications based on the point estimates of the thresholds.

For the 3-month tenor, the low and high threshold estimates from the TVEC model are 38 and 82 basis points, respectively as can be seen in Table 5, panel a. Consistent with higher volatility

[11] When lag order is selected based on information criteria, results are qualitatively similar and available upon request.

[12] Akaike and Schwarz information criteria provide identical results.

associated with elevated stress levels, the width of the symmetric confidence band around the high threshold estimate is about 30 basis points compared with only 16 basis points for that of the low threshold. The noticeably lower high threshold estimate from the SETAR model, shown in panel b, also emphasizes the higher uncertainty surrounding this parameter. In contrast, the two alternative modeling strategies yield identical estimates for the first stress threshold.

In terms of economic interpretation, the first regime can be regarded as a state of normal market functioning in which the spread fluctuates at relatively subdued levels. The second regime is characterized by an increase in funding pressures and reduced risk appetite. Such pressures intensify further in the third regime with increased risk of market dysfunction. Consistent with the characterization in the theoretical model by Heider et al. (2015), the first regime corresponds to the full-participation equilibrium with subdued interest rates, while the second and third can be considered as states of adverse selection with higher interest rates and complete market breakdown, respectively. Because Libor is a reported rate, the third regime can be associated with either very limited lending activity or a complete market freeze. Estimates are consistent with a similar interpretation in case of the 1- and 6-month tenors.

Regime classification over time differs notably across the tenors. At the 1-month horizon, the third regime prevails relatively more frequently with brief switches in and out of the second regime. (Figure 4). At the longest end of the maturity spectrum, the first regime is not a recurrent phenomenon but an almost exclusive characterization of the pre-crisis period, as can be seen from Figure 6, panel b. That is, the classification at the 6-month horizon obtained from the TVEC model suggests a permanent structural break in August 2007. As a result, we focus on the 3-month horizon in order to obtain a historical regime classification.

The timing and duration of regimes at the 3-month horizon are consistent with the economic interpretation discussed above. The first regime of subdued spread levels prevails from the beginning of the sample until the week of August 9, 2007 when BNP Paribas made the aforementioned announcement (Figure 5, panel b). The second regime dominated the following period until the widespread turmoil triggered by the Lehman Brothers bankruptcy in September 2008. The spread reached record highs next month and then started declining from mid-October, following the announcement of recapitalization of banks under the TARP, government guarantees on newly issued bank debt, and temporary expansion of the FDIC deposit insurance to all noninterest bearing deposits.[13] Meanwhile the liquidity provided by the Fed through several facilities reached unprecedented levels.[14]

The risk premia sufficiently declined and the system reverted back to the second regime at the end of April 2009. The switch back to the second regime occurred around the time when the Fed released the framework for the Supervisory Capital Assessment Program (SCAP) and the detailed results from this exercise.[15] Release of the SCAP results seemed to reduce the uncertainty about the health of the banking system. By mid-2009, the end of the recession according to the NBER, the Libor-OIS spread reached levels consistent with the first regime associated with smooth market functioning.

After mid-2009, there were a few instances of relatively elevated spreads driven by developments in credit markets or changes in regulations. The spread approached the lower bound of the confidence band for the first threshold in mid-2010, around the time when the Greek government debt was downgraded to junk-bond status. The spread exceeded the estimated first threshold in late-2011 amid increased financial distress in Europe due to the sovereign debt crisis. More recently, there has been an increase in the Libor-OIS spreads leading up to compliance date of the money fund reform in October 2016.[16] Money funds reduced appetite for term lending likely pushed liquidity premiums up and led to higher Libor-OIS spreads. This is marked by a switch from the low- to moderate-stress regime in August 2016 in our model. As the banking system adjusted to the new reality, the system reverted back to the subdued-spread regime at the end of October. According to a more conservative estimate based on the interval estimates, this adjustment took a few months longer. Around the time when the Libor-OIS spread started to widen due to term funding pressures in response to the upcoming changes in the rules, it was not clear whether this would imply a permanent change in the pricing of term funding. An important takeaway from our results for this recent episode is that, rather than a permanent structural break, the elevated spread most likely reflected a transitory switch to a moderate-stress regime.

[13] See Veronesi and Zingales (2010) for a detailed discussion of the TARP and the guarantee programs as well as their impact on bank valuations.

[14] Fleming (2012) examines liquidity provision by the Fed during the crisis and surveys the evidence on its effectiveness.

[15] See Hirtle et al. (2009) for a detailed discussion of the SCAP and its impact.

[16] Changes to the Securities and Exchange Commission rules regulating money market mutual funds (MMFs) went into effect on October 14, 2016. See Chen et al. (2017) for a detailed discussion of these changes and their effect on the money fund industry.

4.3 Regime-dependent Equilibrium Dynamics

For the 1-month tenor, the system has a tendency to revert back to equilibrium only in the first and third regimes, as can be seen from Table 6. Although both rates respond to the error correction term in the same direction, the magnitude of adjustment in Libor is larger, leading to mean-reversion in the spread. The adjustment in the low-spread regime is slower; the half-life of a shock implied by the TVEC model is about 16 weeks in the low-spread regime while it is 7 weeks in the high-spread regime. Estimates based on the first order SETAR model fitted to the spread, shown in Table 9, also suggest a somewhat slower adjustment in the first regime. There is practically no response by either Libor or OIS to the spread in the middle regime, i.e. no tendency for the system to move toward equilibrium. Indeed, the SETAR model indicates that the spread behaves like a unit-root process in the middle regime. Figure 7 shows responses to the error correction term based on estimated intercepts and speed of adjustment parameters as in Hansen and Seo (2002). The spread tends to increase up to 1.65% in the third regime, as reflected in the positive and statistically significant estimate of the Libor drift, and mean reversion kicks in afterwards (panel a). This implied regime-dependent equilibrium level of the spread is substantially above the actual sample mean of 1.05% in the third regime.

As can be seen from Table 7, the gap between the Libor and OIS adjustment coefficients across the low- and high-spread regimes is notably greater for the 3-month tenor than in the 1-month case. The middle regime is characterized by a slow adjustment toward equilibrium although it is not statistically significant. The implied half-life of a shock in the first regime is about a year according to the TVEC parameter estimates. The regime-dependent persistence parameter estimate from the SETAR model also concurs. In contrast, the implied half-life is 6 to 14 weeks in the high-spread regime across the models. The estimated response functions for the 3-month horizon, shown in Figure 7 panel b, indicate a slow mean-reversion for the spread toward 0.17 % in the low-spread regime. The markedly faster mean-reversion driven by Libor in the third regime indicates convergence to a level consistent with the respective sample-mean of the spread.

The equilibrium dynamics in case of the 6-month maturity are different than those for shorter maturities. In the TVEC model, the first-regime corresponds to the pre-crisis period with no meaningful adjustment toward equilibrium (Table 8). The point estimates suggest a slowly mean-reverting system in the middle regime, but the weak economic significance is accompanied by borderline statistical significance. Only in the high-spread regime, there is a statistically and economically significant convergence to a stable equilibrium. The SETAR model paints a different picture due to the aforementioned difference in the low threshold estimate. With an implied half-life of a shock close to 4-years in the low-spread regime, and no material difference between the middle- and high-spread regimes, the SETAR results appear to be less coherent in providing estimates of economically meaningful dynamic adjustments.

Overall, our results indicate that when shocks drive risk premia higher, the adjustment toward equilibrium is also affected, reflecting changes in risk assessment, the role of policy interventions that aim to reduce risk premia, and adjustments by banks to their asset and liability structure.

4.4 Time-varying Volatility and Correlation

Table 10 reports the parameter estimates of the multivariate GARCH models. For OIS, the reaction parameter (α) in the individual GARCH equation decreases slightly as maturity increases from 1-month to 6-months, while the decrease in case of the risky funding rate, Libor, is rather dramatic: the estimated parameter goes down from about 0.7 at 1-month tenor to 0.23 at 6-months. Moreover, the coefficient of the lagged variance term (β) tends to get larger as maturity increases for both rates. The overall volatility persistence ($\alpha + \beta$) also increases with maturity in case of both OIS and Libor.

The regime-dependent volatility estimates for the OIS and Libor are almost identical in the low-spread state and fairly close to each other in the intermediate one. However, the volatility drift for Libor moves up substantially in the third regime for all maturities. Therefore, our estimates indicate that the uncertainty surrounding the liquidity and credit risk components of Libor increase dramatically as the level of the spread rises above certain endogenous threshold.

Conditional volatilities of both Libor and OIS rates increased to unprecedented levels during the financial crisis at all maturities (Figure 8). As indicated by regime-dependent estimates of the volatility drifts, the gap between Libor and OIS volatilities is the largest in the high-spread regime. Volatilities also increased notably in the aftermath of the crisis during times of elevated uncertainty in the offshore U.S. dollar funding markets in 2010 and 2011, but such increases were considerably smaller than the movements observed at the height of the crisis. Prior to the federal funds rate hikes in December 2015 and March 2017, both Libor and OIS volatilities were elevated likely reflecting the anticipation of higher rates as well as the uncertainty around the exact timing. Meanwhile, the Brexit referendum and money fund reform contributed to significantly higher volatility in the second half of 2016.

The underlying rates tend to exhibit moderate to large positive correlation in the regime associated with normal market functioning. As funding stress builds up, notable declines in the correlations are observed at 3- and 6-month maturities. In case of the 3-month tenor, the regime-dependent correlation between Libor and OIS innovations declines substantially as the spread breaches the first threshold and then turns negative in the third regime when funding stress reaches very highest levels.

4.5 Extensions

We extend our analysis to check robustness of the results in two crucial dimensions. We limit the sample period to assess the effects of potential structural changes and consider transaction-based rates instead of the *reported* Libor.

The transaction-based measures are obtained from derivatives contracts where Libor serves as the reference rate. The first one is based on forward rate agreements (FRA). A FRA is essentially an interest rate swap that determines the rate of interest between parties to be paid or received on an obligation beginning at a future date. It involves a single cash flow where the floating leg is referenced to the Libor.[17] We focus on the so-called 3x6 FRA in which the underlying rate is 3-month Libor three months into the future. The spread is calculated relative to the 3-month OIS, 3-month forward. Our second measure is the spread between the fixed rate on a 2-year interest rate swap (IRS) with floating leg payment indexed to the 3-month Libor and the OIS rate of the same maturity, which is adapted from Filipović and Trolle (2013). Both of these alternative measures reflect market expectations of the Libor-OIS spread under risk neutrality. That is, if the FRA-OIS (or IRS-OIS) spread is higher than the Libor-OIS spread, then market participants either expect the latter to increase or require a large risk premium for bearing future interbank risk or both.

[17] See Stigum and Crescenzi (2007) for further details on FRA contracts.

Credit and liquidity risks were discretely repriced in August 2007 as we discussed above. This change in risk assessment persisted through the crisis and possibly during its aftermath. Moreover, banks faced a more stringent regulatory environment in the post-crisis period amid implementation of the Basel III capital and liquidity requirements, mandatory annual stress tests, and other rules introduced under the Dodd-Frank Act. As a result, analyzing the subsample since August 2007 may provide further insights in addition to serving as a robustness check to our full-sample results.

Table 11 reports the threshold estimates from for 3-month Libor-OIS, FRA-OIS and IRS-OIS pairs from the restricted sample that begins on August 9, 2007. For Libor-OIS, the threshold estimates are 12-15 basis points larger than those obtained from the full-sample, mainly reflecting the relatively elevated average of the spread during the crisis and its aftermath. As a result, the regime classification with respect to the point estimates are slightly different as can be seen from Figures 5 and 9. The lower bounds of the interval estimates for the restricted sample are almost identical to the full-sample point estimates, resulting in regime classifications that are essentially the same as before. Additionally, the threshold estimates for Libor-OIS are fairly close between the TVEC and SETAR models. Overall, our key conclusions for the 3-month Libor-OIS are robust to eliminating pre-crisis data from the estimation.

The threshold estimates for FRA-OIS and IRS-OIS spreads and the resulting regime classification are largely consistent with the results obtained from the Libor-OIS data. The regime classifications for the two spreads indicate a short period of moderate stress in 2010, around the time when first signs of the Greek debt crisis emerged, and also in the second half of 2011 when the sovereign debt crisis in Europe intensified amid contagion from Greece to other peripheral economies. None of the classifications in the restricted sample indicate a shift to a moderate stress regime due to the money market fund reform, standing in contrast to the classification implied by the 3-month Libor-OIS in the full sample. Only when we consider the lower bounds of the interval estimates obtained from Libor-OIS and FRA-OIS spreads, we conclude that the money fund reform resulted in a brief period of stress due to tighter funding conditions. Interestingly, the IRS-OIS spread, which takes a medium-term view of the interbank market, does not indicate a period of material stress even after taking into account the uncertainty surrounding the point estimates for the stress thresholds. This finding is consistent with the idea that even if market participants anticipated some difficulties for banks' term funding due to the reform, such pressures were not expected to persist beyond horizons of a few months.

Regime-dependent equilibrium dynamics for the 3-month Libor-OIS pair are similar to the full-sample case, as can be seen from Table 12. The first regime is characterized by very persistent shocks and a slow adjustment toward equilibrium. Parameter estimates in the first regime are less precise in the restricted sample, while the magnitude and statistical significance of the error correction coefficients in the high-spread regime are very similar across the two samples. The implied half-life of a shock is 5 months in the restricted sample, compared with 6 months in the full-sample. Among the market-based measures, results for the IRS-OIS spread are generally in line with the Libor-OIS case (Table 14). The spread appears to be a near-integrated process in the first regime while it is subject to significant mean-reversion in high-spread regime (Table 13 and Figure 12 panel c). However, one difference is that the half-life of a shock, at slightly less than 2 months, is notably shorter in the IRS-OIS system, likely reflecting the medium-term focus of this measure. Therefore, we conclude that the FRA-OIS and IRS-OIS spreads, especially the latter, provide useful alternatives to the Libor-OIS to gauge stress and relative levels of risk premia in the term interbank funding markets.

5 Concluding Remarks

Motivated by developments in the interbank funding markets over the past decade and the growing theoretical literature, we model dynamics in these markets in a nonlinear empirical framework. We estimate threshold error correction models for the Libor and OIS rates that incorporate their long-run equilibrium relationship as well as state dependent dynamics of their spread. In our models, the Libor-OIS spreads serve as both equilibrium correction terms and the threshold variables identifying regimes with different characteristics. We identify three distinct regimes that resemble different equilibrium outcomes associated with varying levels of leverage, asset quality, and liquidity in the banking system. We provide point and interval estimates for spread thresholds which serve as potential benchmarks for policy makers and market participants to assess funding conditions. Our results also indicate strong asymmetry in the equilibrium adjustment mechanism, with long-run relationships breaking down in periods of moderate stress. The most economically significant adjustments take place in regimes associated with high risk spreads, likely reflecting a combination of market response to repricing of risk, and policy intervention that aim to reduce credit and liquidity risk premia. Our results are robust to using transactions-based data instead of Libor or excluding the pre-crisis period from estimation.

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Tables and Figures

Table 1: Descriptive Statistics for Libor-OIS Spreads

	1-month	3-month	6-month
	Panel a: Jan. 2002 – Jun. 2007		
Mean	8.8	11.0	12.1
IQR	4.2	4.8	6.8
AC(1)	0.89	0.92	0.93
	Panel b: Jul. 2007 – Jun. 2009		
Mean	55.7	89.2	108.1
IQR	34.5	37.4	72.1
AC(1)	0.92	0.95	0.97
	Panel c: Jul. 2009 – Mar. 2017		
Mean	8.6	20.3	38.4
IQR	4.1	14.0	26.6
AC(1)	0.96	0.99	0.99
	Panel d: Jan. 2002 – Mar. 2017		
Mean	14.8	25.9	38.0
IQR	5.1	16.3	36.6
AC(1)	0.95	0.98	0.99

Notes: Data are weekly. Mean and interquartile range (IQR) are reported in basis points. AC(1) denotes first order autocorrelation.

Table 2: Unit Root Tests for Interest Rates and Spreads

	ERS Test	NP Test
	Panel a: Interest Rates	
1-month Libor	8.06	8.04
3-month Libor	11.68	11.67
6-month Libor	8.32	8.33
1-month OIS	5.69	5.65
3-month OIS	9.65	9.61
6-month OIS	11.58	11.54
	Panel b: Spreads	
1-month Libor-OIS	0.26	0.26
3-month Libor-OIS	1.13	1.13
6-month Libor-OIS	2.56	2.55
	Critical Values	
1%	1.99	1.78
5%	3.26	3.17
10%	4.48	4.45

Notes: ERS Test and NP Test denote test statistics of Elliott et al. (1996) and Ng and Perron (2001) respectively. Data are weekly and the sample runs from January 1, 2002 to March 22, 2017.

Table 3: Threshold Nonlinearity Tests for Libor-OIS Pairs

T_0	1-month	3-month	6-month
57	0.072	0.001	0.002
85	0.077	0.003	0.002
113	0.076	0.004	0.002
141	0.105	0.006	0.005

Notes: p-values associated with the threshold nonlinearity test statistics of Tsay (1998) are reported for the null hypothesis of a first-order-linear VEC model. T_0 denotes size of the initiation sample for computation of recursive residuals. Data are weekly and the sample runs from January 1, 2002 to March 22, 2017.

Table 4: Model Selection for Libor-OIS Pairs

	1-month	3-month	6-month
Linear VEC	-6.7498	-7.1563	-6.9411
2-regime TVEC	-9.0798	-8.4117	-7.8774
3-regime TVEC	-9.7180	-9.4643	-8.0842

Notes: Hannan-Quinn model selection criterion for linear and threshold VEC models with $p = 1$ are reported. Data are weekly and the sample runs from January 1, 2002 to March 22, 2017.

Table 5: Threshold Estimates for Libor-OIS Spreads

	$CI_L(\gamma_1)$	$\widehat{\gamma}_1$	$CI_U(\gamma_1)$	$CI_L(\gamma_2)$	$\widehat{\gamma}_2$	$CI_U(\gamma_2)$
	Panel a: TVEC Model					
1-month	9.8	15.7	21.5	38.8	45.7	52.7
3-month	30.3	38.2	46.1	67.0	82.2	97.4
6-month	9.8	19.4	29.0	85.9	100.3	114.6
	Panel b: SETAR Model					
1-month	9.6	15.3	21.0	31.7	45.7	59.7
3-month	31.4	38.2	44.9	45.8	59.6	73.4
6-month	51.5	61.0	70.4	92.9	105.2	117.5

Notes: Threshold estimates ($\widehat{\gamma}$) and 90% subsampling confidence intervals (in basis points) are reported for TVEC and SETAR models with $p = 1$. Data are weekly and the sample runs from January 1, 2002 to March 22, 2017.

Table 6: TVEC Model for the 1-month Libor-OIS Pair

Parameter	Regime 1	Regime 2	Regime 3
c_1	0.005	0.006	-0.008
	(0.09)	(0.43)	(0.63)
c_2	0.009	0.002	0.139
	(0.00)	(0.86)	(0.00)
a_{11}	0.839	0.809	0.188
	(0.00)	(0.00)	(0.16)
a_{12}	-0.253	-0.015	-0.028
	(0.20)	(0.89)	(0.26)
a_{21}	0.608	0.767	0.596
	(0.00)	(0.00)	(0.08)
a_{22}	0.027	0.073	0.568
	(0.91)	(0.59)	(0.00)
ϕ_1	-0.028	-0.038	-0.055
	(0.39)	(0.26)	(0.00)
ϕ_2	-0.070	-0.024	-0.147
	(0.01)	(0.65)	(0.00)

Notes: Parameter estimates and p-values based on Newey and West (1987) HAC standard errors are reported for the three-regime TVEC model. Data are weekly and the sample runs from January 1, 2002 to March 22, 2017. Subscript 1 indicates OIS and 2 indicates Libor.

Table 7: TVEC Model for the 3-month Libor-OIS Pair

Parameter	Regime 1	Regime 2	Regime 3
c_1	0.006	-0.005	0.058
	(0.01)	(0.81)	(0.00)
c_2	0.008	0.017	0.191
	(0.00)	(0.55)	(0.03)
a_{11}	0.715	0.503	0.167
	(0.00)	(0.00)	(0.11)
a_{12}	-0.115	0.172	-0.049
	(0.40)	(0.32)	(0.31)
a_{21}	0.527	0.399	-0.451
	(0.01)	(0.00)	(0.32)
a_{22}	0.077	0.563	0.601
	(0.70)	(0.00)	(0.00)
ϕ_1	-0.023	-0.008	-0.072
	(0.03)	(0.82)	(0.00)
ϕ_2	-0.036	-0.026	-0.180
	(0.01)	(0.63)	(0.00)

Notes: Parameter estimates and p-values based on Newey and West (1987) HAC standard errors are reported for the three-regime TVEC model. Data are weekly and the sample runs from January 1, 2002 to March 22, 2017. Subscript 1 indicates OIS and 2 indicates Libor.

Table 8: TVEC Model for the 6-month Libor-OIS Pair

Parameter	Regime 1	Regime 2	Regime 3
c_1	0.035	0.001	0.078
	(0.00)	(0.62)	(0.02)
c_2	0.035	0.005	0.337
	(0.00)	(0.22)	(0.00)
a_{11}	1.090	0.377	0.288
	(0.00)	(0.00)	(0.03)
a_{12}	-0.793	0.206	-0.086
	(0.00)	(0.16)	(0.19)
a_{21}	1.202	0.100	-0.912
	(0.00)	(0.22)	(0.00)
a_{22}	-0.819	0.588	0.481
	(0.00)	(0.00)	(0.00)
ϕ_1	-0.232	-0.007	-0.068
	(0.00)	(0.38)	(0.00)
ϕ_2	-0.225	-0.014	-0.245
	(0.00)	(0.22)	(0.00)

Notes: Parameter estimates and p-values based on Newey and West (1987) HAC standard errors are reported for the three-regime TVEC model. Data are weekly and the sample runs from January 1, 2002 to March 22, 2017. Subscript 1 indicates OIS and 2 indicates Libor.

Table 9: SETAR Model for Libor-OIS Spreads

	1-month	3-month	6-month
μ_1	0.005	0.003	0.002
	(0.00)	(0.12)	(0.30)
κ_1	0.944	0.985	0.997
	(0.00)	(0.00)	(0.00)
μ_2	-0.001	-0.158	0.076
	(0.94)	(0.12)	(0.13)
κ_2	1.000	1.369	0.897
	(0.00)	(0.00)	(0.00)
μ_3	0.100	0.039	0.113
	(0.10)	(0.48)	(0.14)
κ_3	0.888	0.954	0.930
	(0.00)	(0.00)	(0.00)

Notes: Parameter estimates for the SETAR model with $p = 1$. Data are weekly and the sample runs from January 1, 2002 to March 22, 2017.

Table 10: Multivariate GARCH Model for Libor-OIS Pairs

	1-month	3-month	6-month
α_1	0.365	0.327	0.224
	(0.00)	(0.00)	(0.00)
α_2	0.691	0.442	0.232
	(0.00)	(0.00)	(0.00)
β_1	0.555	0.632	0.766
	(0.00)	(0.00)	(0.00)
β_2	0.169	0.501	0.758
	(0.00)	(0.00)	(0.00)
$\sigma_{1,1}$	0.019	0.021	0.039
$\sigma_{2,1}$	0.018	0.020	0.034
$\sigma_{1,2}$	0.051	0.066	0.037
$\sigma_{2,2}$	0.061	0.075	0.039
$\sigma_{1,3}$	0.075	0.052	0.056
$\sigma_{2,3}$	0.248	0.176	0.138
ρ_1	0.263	0.594	0.894
ρ_2	0.441	0.421	0.515
ρ_3	-0.133	-0.083	0.210

Notes: p-values for GARCH parameters are based on Bollerslev and Wooldridge (1992) robust standard errors. Subscript 1 indicates OIS and 2 indicates Libor. For regime-dependent parameters ($\sigma_{i,j}$ and ρ_j), i indexes rates j indexes regimes. Data are weekly and the sample runs from January 1, 2002 to March 22, 2017.

Table 11: Threshold Estimates in the Restricted Sample

	$CI_L(\gamma_1)$	$\widehat{\gamma}_1$	$CI_U(\gamma_1)$	$CI_L(\gamma_2)$	$\widehat{\gamma}_2$	$CI_U(\gamma_2)$
	Panel A: TVEC Model					
Libor-OIS	40.6	50.2	59.9	80.8	97.7	114.6
FRA-OIS	34.5	43.3	52.2	53.1	63.0	72.8
IRS-OIS	40.8	44.3	47.7	62.1	68.6	75.1
	Panel B: SETAR Model					
Libor-OIS	42.1	52.2	62.3	82.2	92.7	103.1
FRA-OIS	37.6	46.0	54.4	75.1	84.2	93.3
IRS-OIS	39.0	44.9	50.9	62.4	69.0	75.6

Notes: Threshold estimates and 90% subsampling confidence intervals (in basis points) are reported for TVEC and SETAR models with $p = 1$. Data are weekly and the sample runs from August 9, 2007 to March 22, 2017.

Table 12: TVEC Model for the 3-month Libor-OIS Pair in the Restricted Sample

Parameter	Regime 1	Regime 2	Regime 3
c_1	0.000	-0.080	0.082
	(0.90)	(0.12)	(0.00)
c_2	0.002	0.077	0.292
	(0.24)	(0.32)	(0.02)
a_{11}	0.357	0.319	0.045
	(0.00)	(0.05)	(0.67)
a_{12}	0.408	-0.033	-0.044
	(0.01)	(0.73)	(0.39)
a_{21}	0.246	0.285	-0.390
	(0.10)	(0.14)	(0.36)
a_{22}	0.530	0.491	0.629
	(0.00)	(0.01)	(0.00)
ϕ_1	0.004	0.077	-0.090
	(0.64)	(0.22)	(0.00)
ϕ_2	-0.007	-0.115	-0.220
	(0.43)	(0.27)	(0.00)

Notes: Parameter estimates and p-values based on Newey and West (1987) HAC standard errors are reported for the three-regime TVEC model. Data are weekly and the sample runs from August 9, 2007 to March 22, 2017. Subscript 1 indicates OIS and 2 indicates Libor.

Table 13: TVEC Model for the 3x6 FRA-OIS Pair in the Restricted Sample

Parameter	Regime 1	Regime 2	Regime 3
c_1	0.011	0.002	0.164
	(0.07)	(0.97)	(0.00)
c_2	0.010	0.180	0.346
	(0.11)	(0.11)	(0.00)
a_{11}	0.173	0.006	0.000
	(0.49)	(0.95)	(1.00)
a_{12}	0.356	-0.020	0.117
	(0.03)	(0.78)	(0.10)
a_{21}	0.098	-0.146	-0.844
	(0.66)	(0.35)	(0.11)
a_{22}	0.472	0.154	0.460
	(0.01)	(0.24)	(0.03)
ϕ_1	-0.058	-0.016	-0.202
	(0.09)	(0.91)	(0.00)
ϕ_2	-0.041	-0.396	-0.418
	(0.21)	(0.09)	(0.00)

Notes: Parameter estimates and p-values based on Newey and West (1987) HAC standard errors are reported for the three-regime TVEC model. Data are weekly and the sample runs from August 9, 2007 to March 22, 2017. Subscript 1 indicates OIS and 2 indicates FRA.

Table 14: TVEC Model for the 2-year IRS-OIS Pair in the Restricted Sample

Parameter	Regime 1	Regime 2	Regime 3
c_1	0.022	0.301	0.521
	(0.03)	(0.01)	(0.00)
c_2	0.023	0.364	0.774
	(0.03)	(0.00)	(0.00)
a_{11}	0.114	-0.399	-0.766
	(0.67)	(0.13)	(0.00)
a_{12}	0.102	0.563	0.316
	(0.75)	(0.01)	(0.05)
a_{21}	-0.055	-0.885	-1.541
	(0.83)	(0.00)	(0.00)
a_{22}	0.279	0.943	0.775
	(0.38)	(0.00)	(0.00)
ϕ_1	-0.108	-0.539	-0.689
	(0.02)	(0.01)	(0.00)
ϕ_2	-0.110	-0.659	-1.009
	(0.02)	(0.00)	(0.00)

Notes: Parameter estimates and p-values based on Newey and West (1987) HAC standard errors are reported for the three-regime TVEC model. Data are weekly and the sample runs from August 9, 2007 to March 22, 2017. Subscript 1 indicates OIS and 2 indicates IRS.

Figure 1: Libor

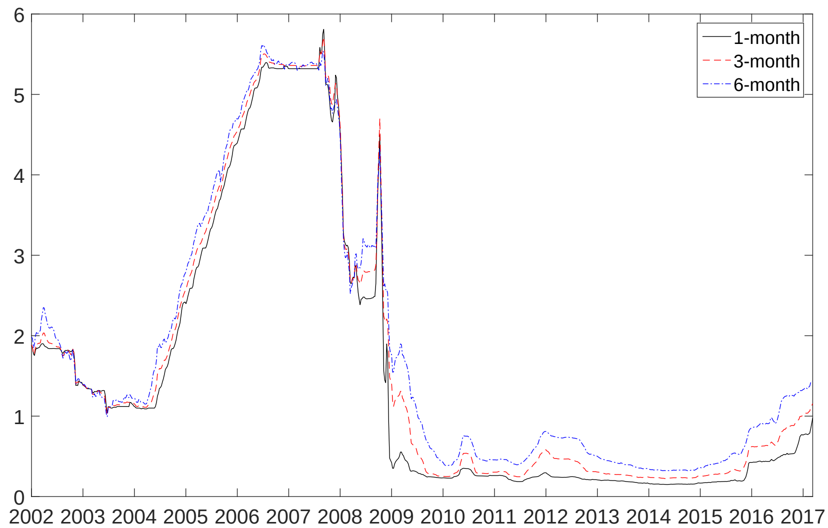
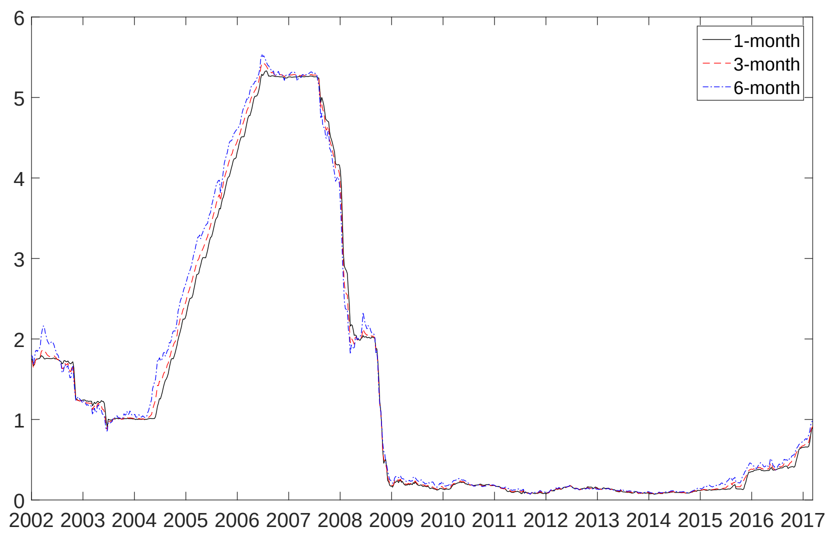
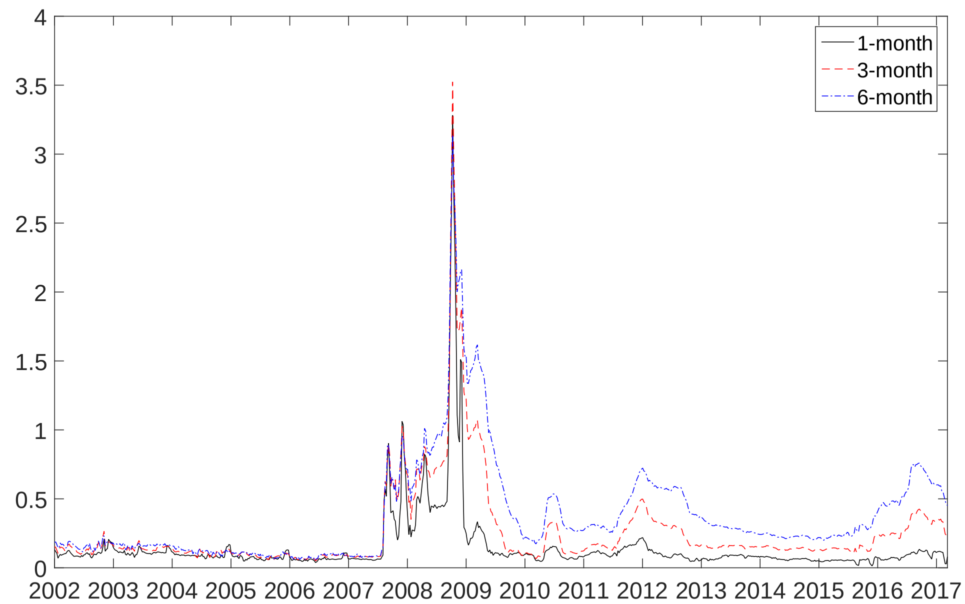


Figure 2: OIS Rates



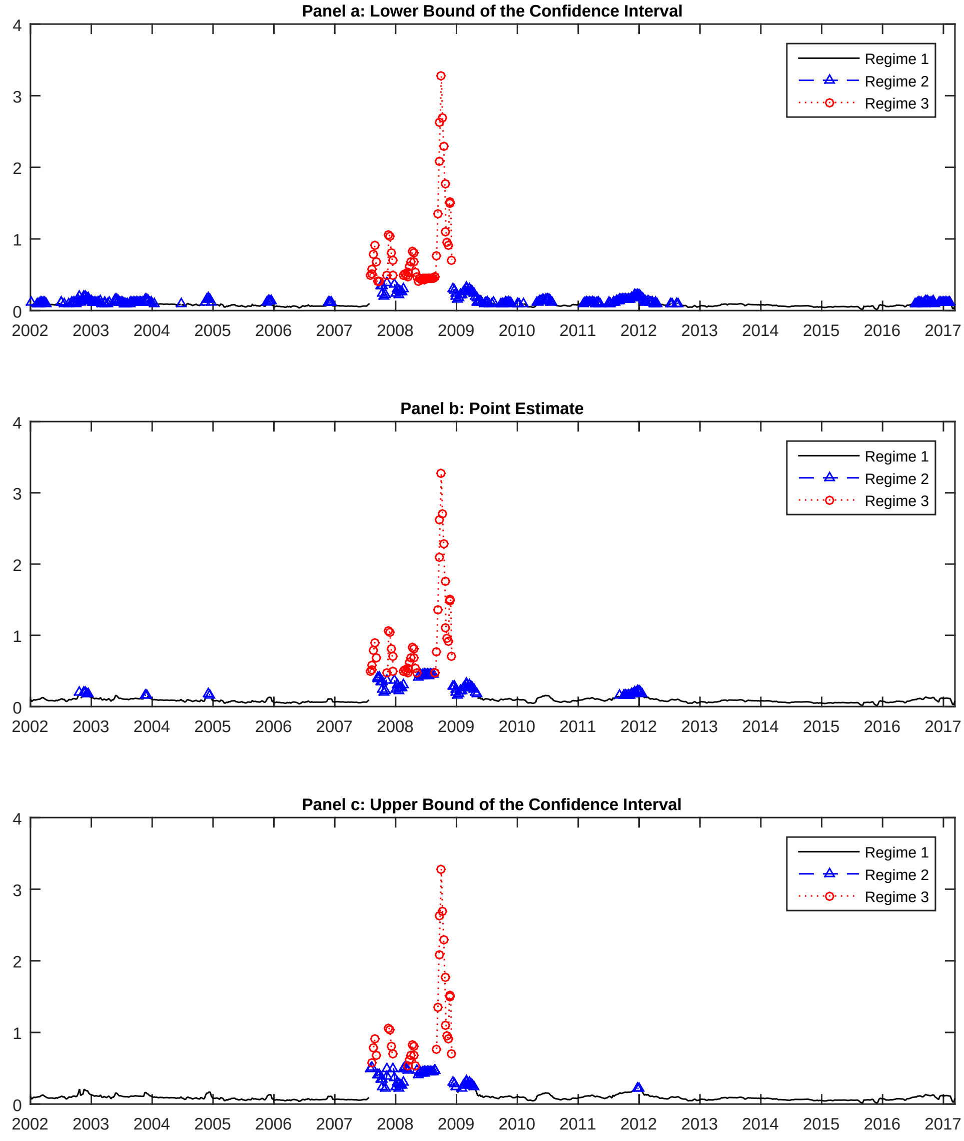
Notes: Data are weekly and the sample runs from January 1, 2002 to March 22, 2017.

Figure 3: Libor-OIS Spreads



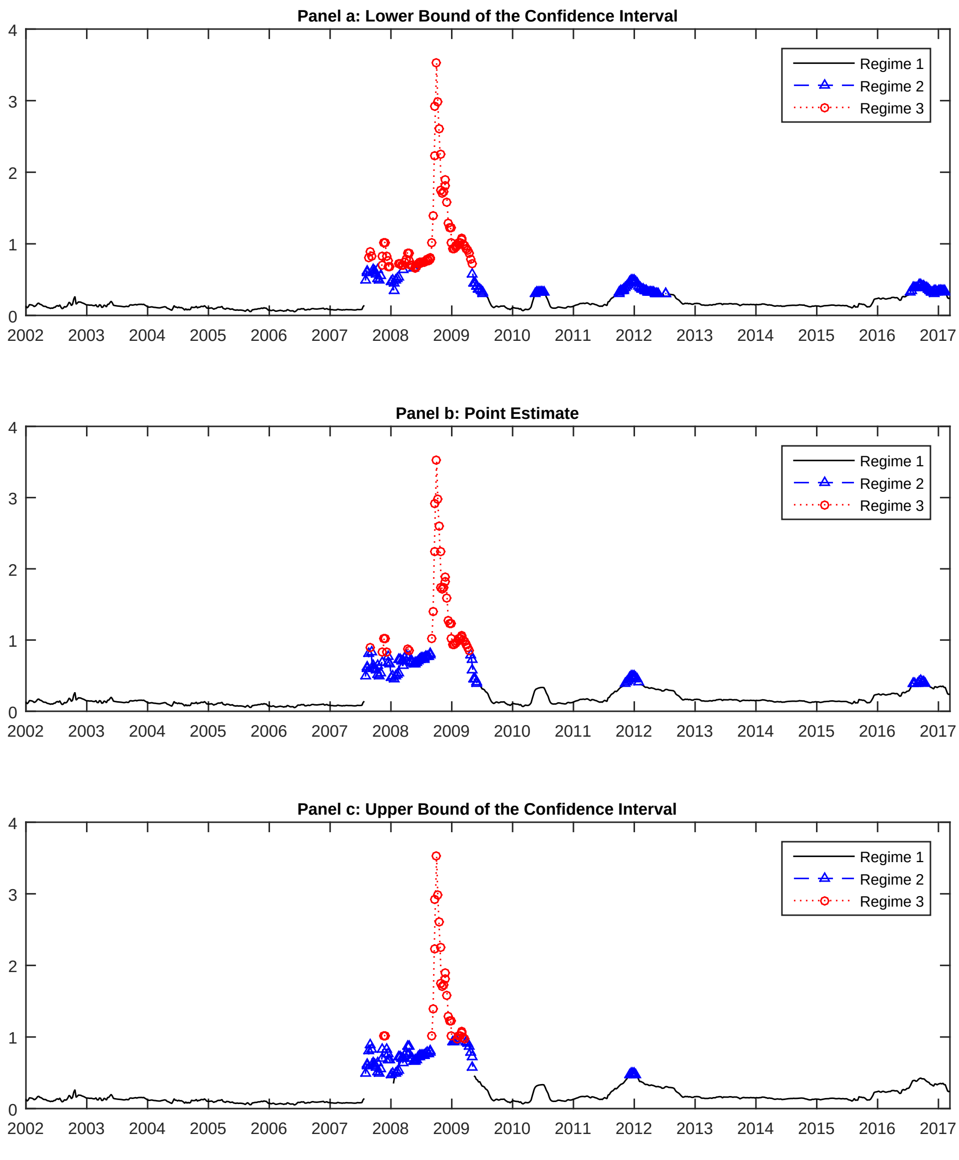
Notes: Data are weekly and the sample runs from January 1, 2002 to March 22, 2017.

Figure 4: Regime Classification from the TVEC Model for the 1-month Libor-OIS Pair



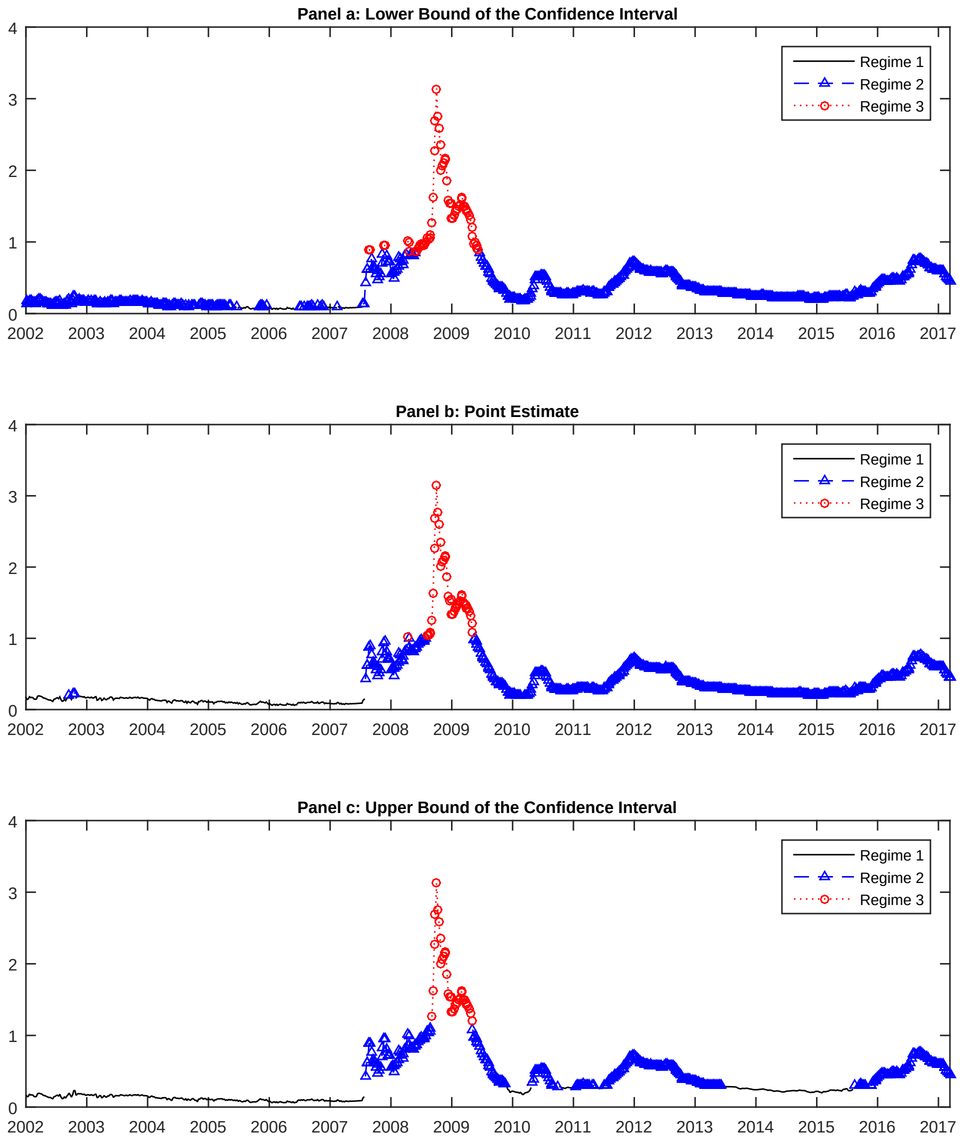
Notes: Data are weekly and the sample runs from January 1, 2002 to March 22, 2017.

Figure 5: Regime Classification from the TVEC Model for the 3-month Libor-OIS Pair



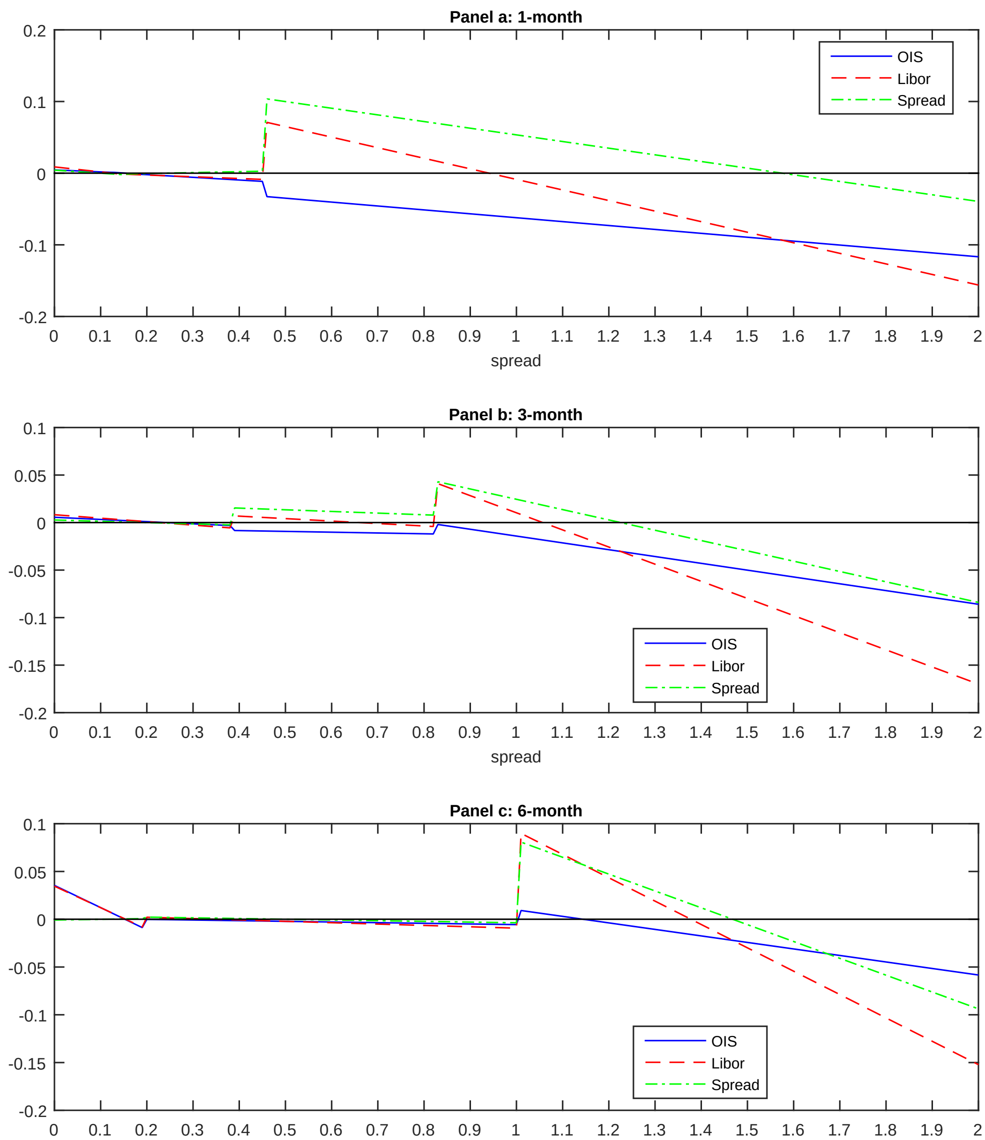
Notes: Data are weekly and the sample runs from January 1, 2002 to March 22, 2017.

Figure 6: Regime Classification from the TVEC Model for the 6-month Libor-OIS Pair



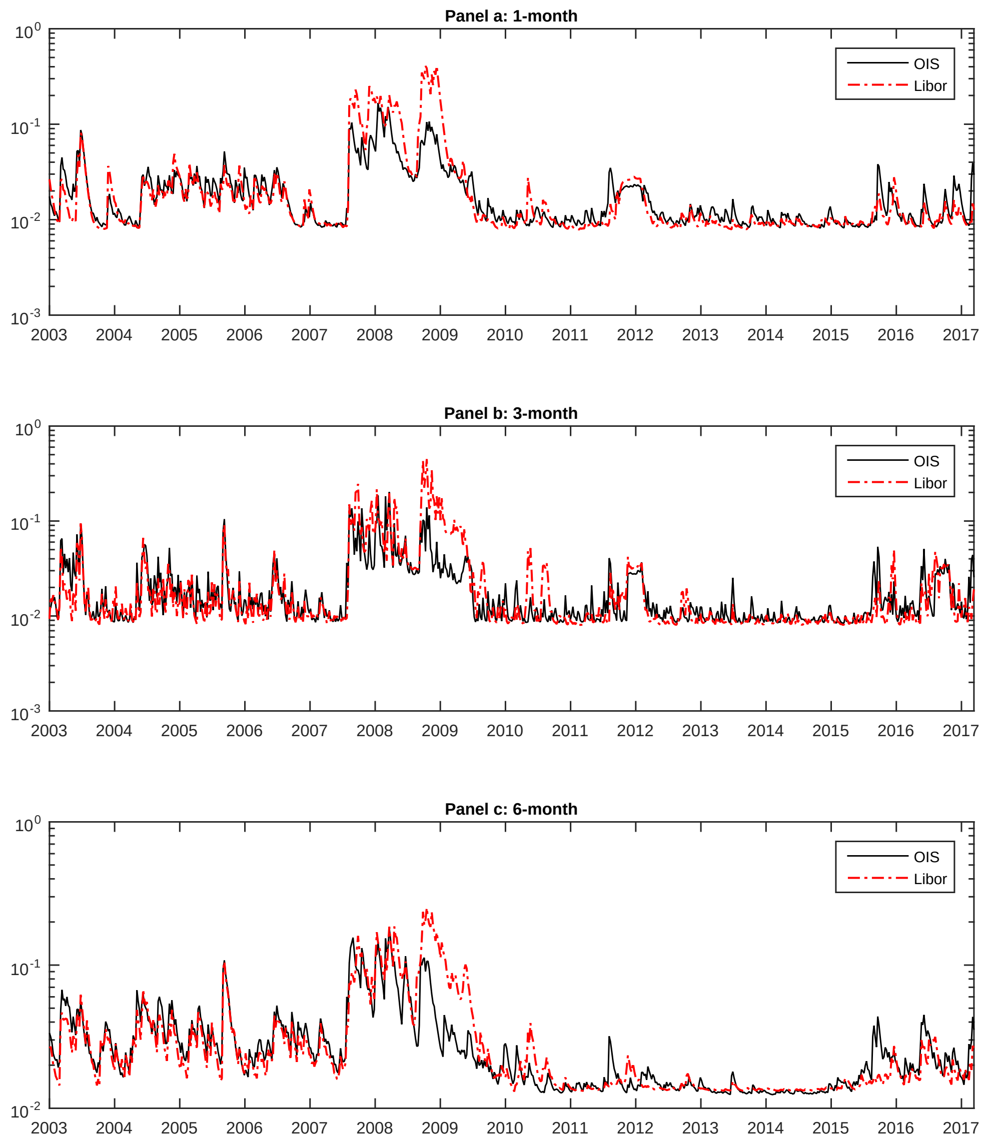
Notes: Data are weekly and the sample runs from January 1, 2002 to March 22, 2017.

Figure 7: Response Functions



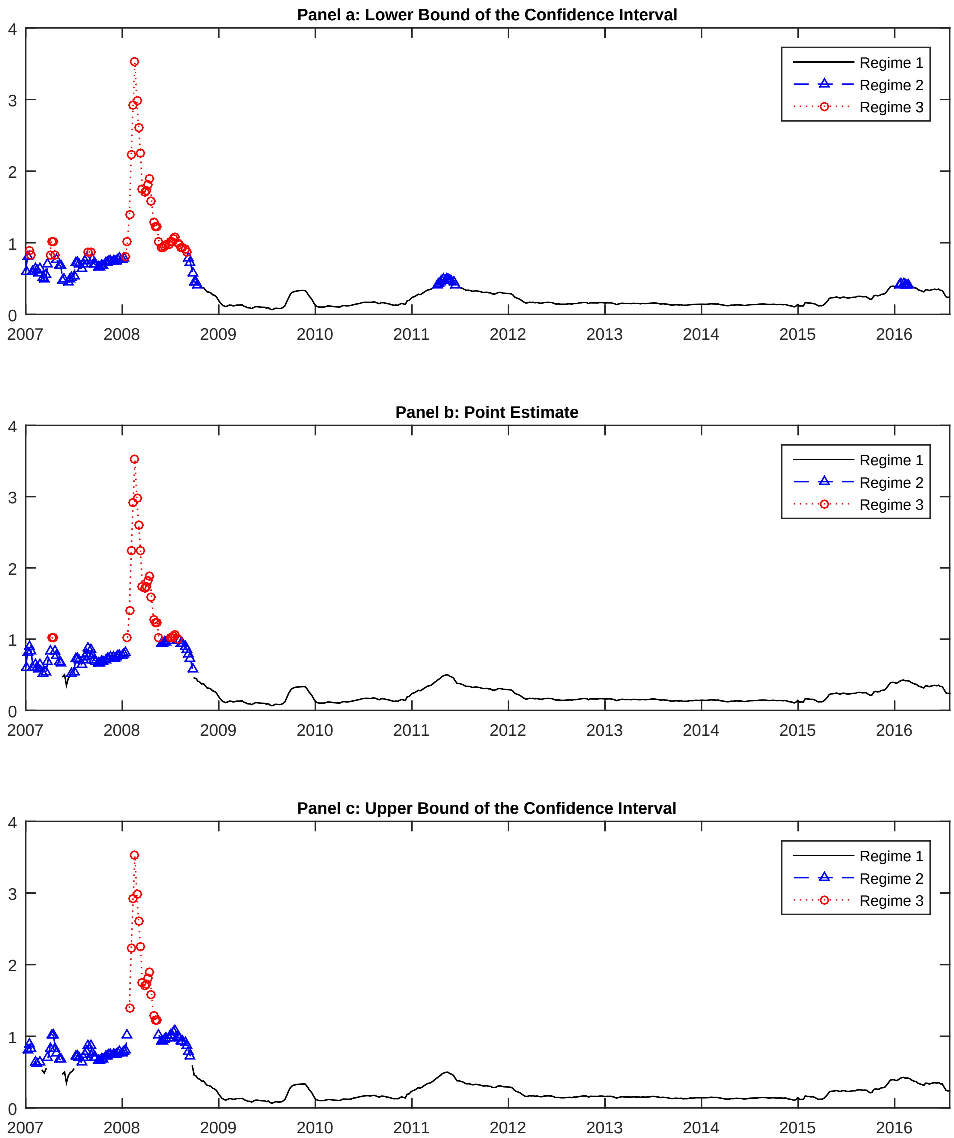
Notes: Response functions are based on the estimated intercept and speed of adjustment parameters.

Figure 8: Estimated Volatility Series for Libor-OIS Pairs



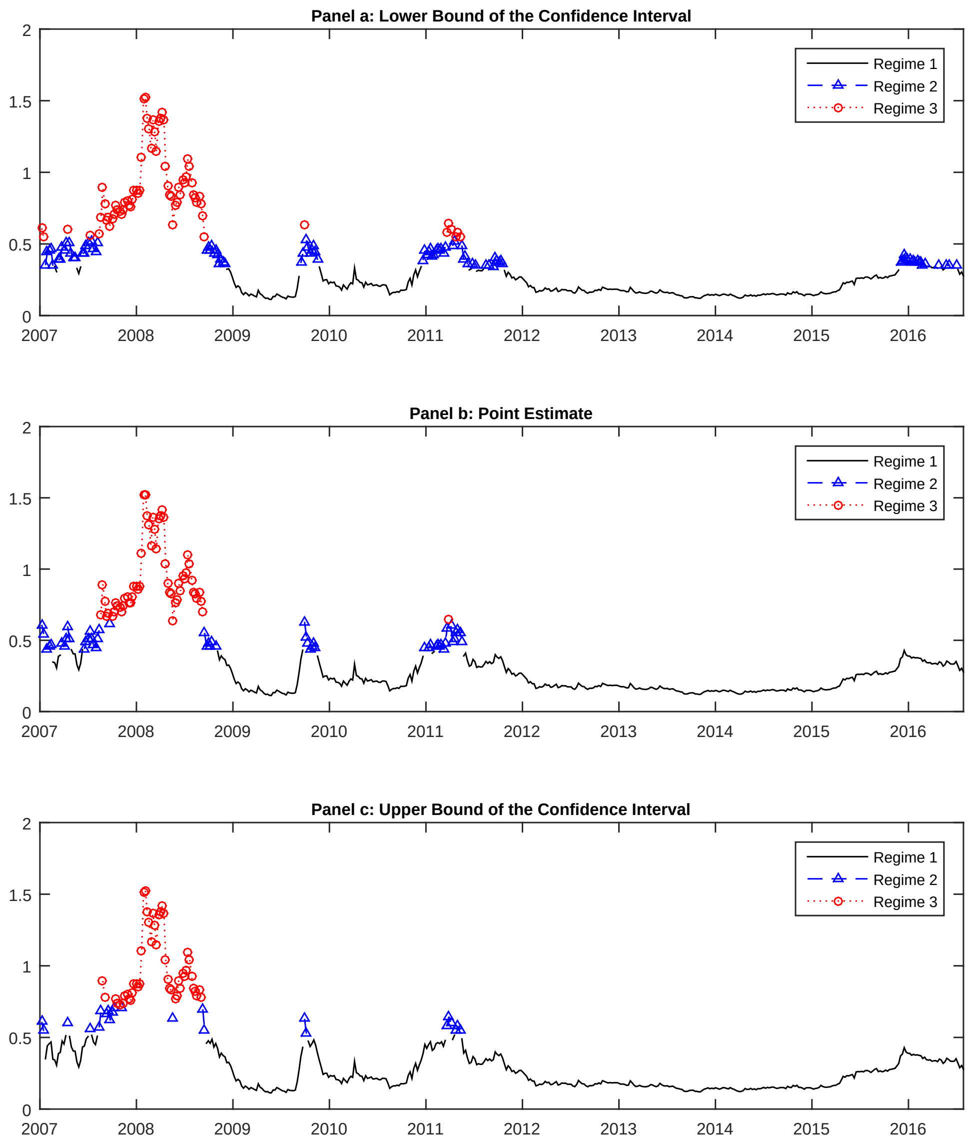
Notes: Weekly volatility series are shown from January 15, 2003 to March 22, 2017 on a log-scale. Volatility estimates are obtained from the threshold-GARCH model described in the text.

Figure 9: Regime Classification from the TVEC Model for the 3-month Libor-OIS Pair in the Restricted Sample



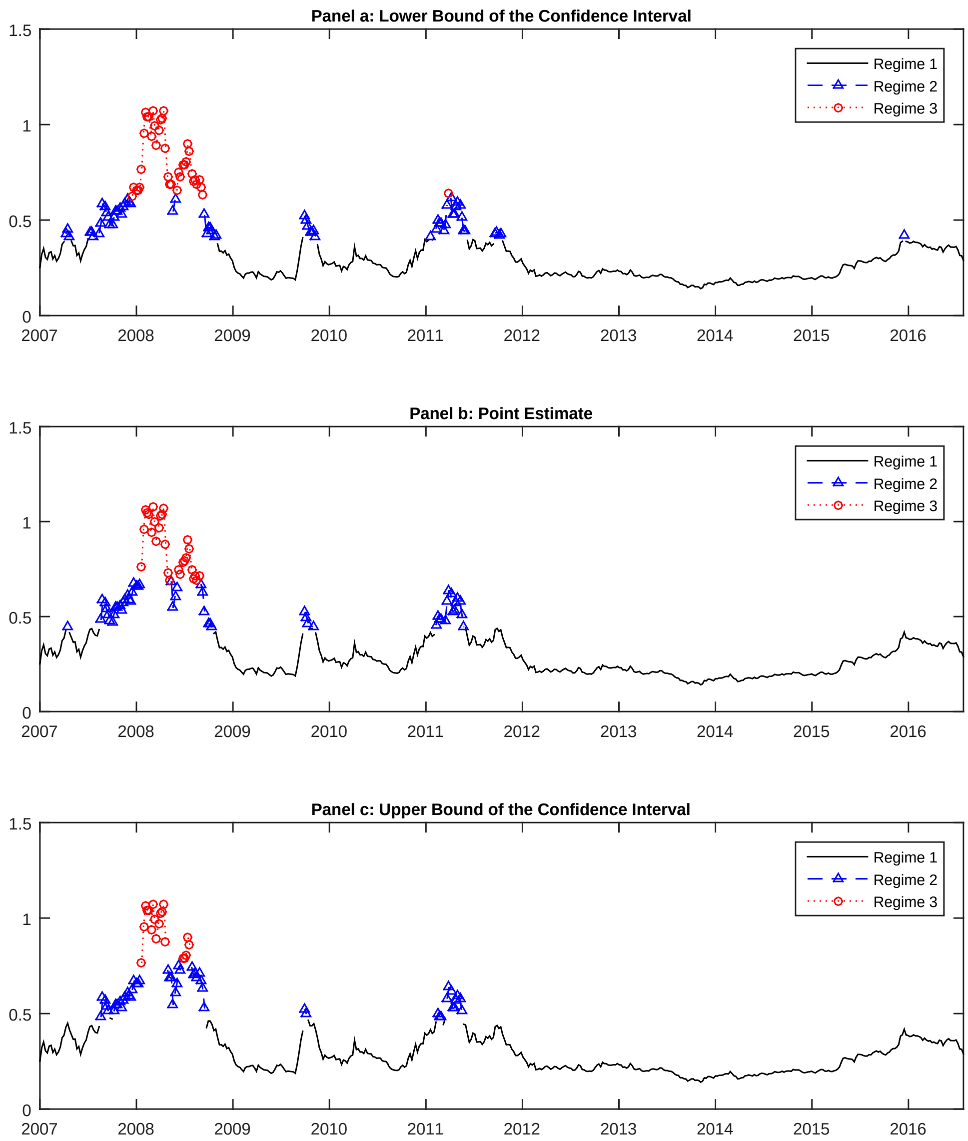
Notes: Data are weekly and the sample runs from August 9, 2007 to March 22, 2017.

Figure 10: Regime Classification from the TVEC Model for the 3x6 FRA-OIS Pair



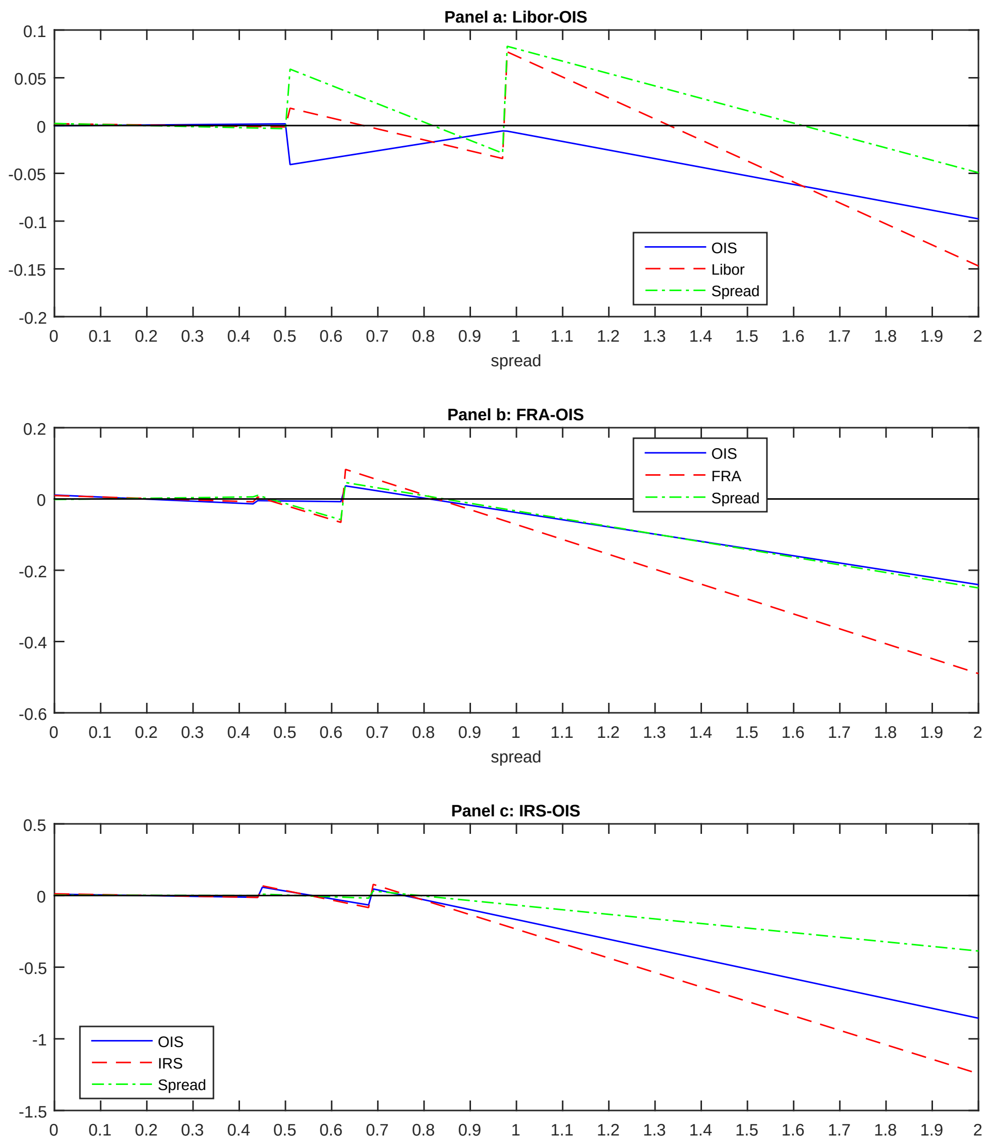
Notes: Data are weekly and the sample runs from August 9, 2007 to March 22, 2017.

Figure 11: Regime Classification from the TVEC Model for the 2-year IRS-OIS Pair



Notes: Data are weekly and the sample runs from August 9, 2007 to March 22, 2017.

Figure 12: Response Functions in the Restricted Sample



Notes: Response functions are based on the estimated intercept and speed of adjustment parameters.