Finance and Economics Discussion Series
Divisions of Research & Statistics and Monetary Affairs
Federal Reserve Board, Washington, D.C.

Financial Stress and Equilibrium Dynamics in Money Markets

Emre Yoldas and Zeynep Senyuz

2015-091

Please cite this paper as:
Yoldas, Emre, and Zeynep Senyuz (2015). "Financial Stress and Equilibrium Dynamics in Money Markets," Finance and Economics Discussion Series 2015-091. Washington: Board of Governors of the Federal Reserve System, http://dx.doi.org/10.17016/FEDS.2015.091.

Financial Stress and Equilibrium Dynamics in Money Markets[*]

Emre Yoldas[†] Zeynep Senyuz[‡]

August 2015

Abstract

Interest rate spreads are widely-used indicators of funding pressures and market functioning in money markets. Using weekly data from 2002 to 2015, we analyze money market dynamics in a long-run equilibrium framework where commonly-monitored spreads serve as error correction terms. We find strong evidence for nonlinearities with respect to levels of the spreads. We provide point and interval estimates for spread thresholds that quantify funding pressure points from a long-run perspective. Our results indicate significant asymmetry in the adjustment toward long-run equilibrium. We show that economically and statistically significant adjustments occur only following large shocks to risk premia. Additionally, we quantify shifts in interest rate volatilities in high spread regimes characterized by elevated funding stress as well as declining correlations between risky funding rates and relatively safe base rates in such environments.

Keywords: Money markets, Cointegration, Threshold models, GARCH, Constant conditional correlation model.

JEL Classification: C32, E44, E52

[*]We would like to thank Beth Klee, Karin Loch, seminar participants at the Federal Reserve Board and American University, participants of the Annual Symposium of the Society for Nonlinear Dynamics and Econometrics, and International Workshop on Financial Markets and Nonlinear Dynamics for useful comments. We thank Francesca Cavalli for preparing the data set. Special thanks to Bernd Schlusche and Selva Demiralp for their contributions to an earlier version of this paper. The views expressed in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or of anyone else associated with the Federal Reserve System.

[†]Federal Reserve Board, Division of Monetary Affairs. E-mail: emre.yoldas@frb.gov

[‡]Federal Reserve Board, Division of Monetary Affairs. E-mail: zeynep.senyuz@frb.gov

1 Introduction

In money markets, a wide array of participants trade highly liquid, short-term, and low-risk debt. Since banks and other financial institutions meet their marginal funding needs in money markets, strains in these markets may impair the flow of credit to the entire economy, e.g. Ivashina et al. (2015). The money market also plays a key role in monetary policy implementation. The Federal Reserve typically relies on the strong comovement between its target rate, the federal funds rate, and other short-term interest rates for effective transmission of its monetary policy.

Until the recent global financial crisis, money market rates were moving in tandem, with generally stable and narrow spreads between them. However, at the onset of the crisis in the summer of 2007, conditions in short-term funding markets changed considerably and persistent spikes in key money market spreads emerged. The Federal Reserve responded to the crisis with a variety of new facilities and unconventional tools, such as the Term Auction Facility, to provide liquidity to the financial system. Following several cuts to its policy rate starting in mid-2007, the Federal Reserve announced a target range of $0 - 0.25\%$ percent for the federal funds rate in December 2008. The federal funds rate and the other overnight funding rates have been near the zero-lower bound (ZLB) since then. In the aftermath of the crisis, abundant reserves in the system, higher risk perception of market participants associated with wholesale funding, and new regulations concerning the management of liquidity risk at large financial institutions have defined the new money market environment.

In this paper, we analyze the dynamic relationship between the interest rates underlying the commonly monitored spreads in short-term funding markets. We estimate vector error correction models (VEC) for pairs of weekly interest rates from January 2002 to July 2015 where the spreads between the rates serve as error correction terms. The VEC framework allows us to capture both the short-run and the long-run dynamics of rates with the stipulation that although spreads may temporarily deviate from longer-run norms, they eventually revert to their equilibrium values due to arbitrage activity or policy intervention. However, it is plausible that such movements toward equilibrium may occur at a different pace or may not even occur depending on the market environment. Therefore, as in Balke and Fomby (1997), we first test for cointegration between the rates, and then explore potential nonlinearities in the long-run relationship.

We find strong evidence in favor of both cointegration and asymmetric dynamics in the relationship between the considered interest rates. Therefore, we estimate a nonlinear version of the VEC model, the so-called threshold VEC model (TVEC), where different states of the market are identified by the level of the spreads that serve as thresholds. This allows us to characterize the discrete adjustment mechanism in the form of threshold cointegration where the cointegrating relation may be muted in a certain range of the relevant spread, but becomes active once the system is sufficiently far away from the equilibrium. We provide estimates and subsampling-based confidence intervals for spread thresholds to quantify funding pressure points from a long-run perspective and determine regimes characterized by different levels of funding stress. In addition, we quantify abrupt shifts in volatilities of interest rates in high spread regimes associated with elevated funding stress. We also show that correlations between risky and relatively safe base rates decline considerably in such regimes.

Our results indicate significant asymmetries in the equilibrium adjustment mechanism, which are masked in a conventional linear model. We find that economically and statistically significant adjustment toward long-run equilibrium occurs following large shocks to risk premia. This result is robust to differences arising from the use of spot and forward rates or the duration of the underlying loans. However, adjustments in relatively low spread environments change with respect to such characteristics. We also find that adjustments can take place through different rates depending on the market segment. For example, in case of the relationship between an interbank term funding rate and the expected policy rate, the adjustment occurs through the former, while the secured rate plays a bigger role in bringing the system back to equilibrium in the case of overnight rates. Our findings on adjustment dynamics are consistent with the combined effects of policy intervention aimed at reducing risk spreads and market response to high levels of compensation for risk. Our results also emphasize the additional information content of forward spreads for risk monitoring as well as the effects of flight-to-quality flows on market dynamics during times of stress.

Our paper is related to two important strands of the literature. First, several studies develop composite indexes that attempt to measure stress in financial markets, see for example, Carlson et al. (2011), Hakkio and Keeton (2009), and Oet et al. (2011) among others. These studies rely on various sets of spreads between rates on risky and riskless assets, liquidity measures, credit flows, as well as implied and realized volatilities to construct composite indicators for measurement of financial stress. Carpenter et al. (2014) develops an index for the money market in a similar framework. In contrast, we analyze different market segments separately in a long-run cointegration framework. This allows us to detect stress that may appear in one part of the market while not being reflected in the funding conditions prevailing in the rest of the market. Moreover, our flexible modeling approach allows us to characterize the evolution of mean, variance and correlation dynamics in different market segments in addition to providing estimates of stress thresholds for market monitoring. Second, our study is also related to the literature that focuses on state dependent comovement in asset prices (see for example Vayanos (2004), He and Krishnamurthy (2012), and Brunnermeier and Sannikov (2014) for theoretical treatments). In this context, we show that the error correction mechanism exhibits asymmetry in different regimes of the money market determined by the risk premia and that correlations between rates are highly state dependent.

The remainder of the paper proceeds as follows: Section 2 describes the data and provides some background information about the key interest rates and the corresponding spreads. Section 3 introduces the econometric framework designed to characterize the evolution of short-run and long-run market dynamics. Section 4 presents and discusses the empirical results. Section 5 concludes.

2 Money Markets: Background

Money market rates tend to move together as overlapping participants in different segments of the market arbitrage away profitable opportunities and central banks take action to prevent decoupling of short-term interest rates. Market frictions or large shocks may lead to temporary divergence of rates from each other resulting in potentially large fluctuations in spreads above and beyond those that can be justified by changes in risk premia determined by the fundamentals. However, over a relatively long period of time average spreads are generally considered as reflecting long-run equilibrium risk premia.

Spreads in money markets can represent different types of risk. In unsecured funding markets, the difference between a term interbank lending rate and the average expected overnight rate over the corresponding period presumably reflects both liquidity and credit risk premia. Such spreads tend to widen when term premia rise as lenders try to shorten tenors or concerns about counterparty risks increase. Therefore, they are typically considered as measures of funding stress. Similarly, the difference between an unsecured rate and a secured rate of return on a safe and highly liquid asset, such as Treasury bills, can be thought of as a measure of both credit and market liquidity risk.

We consider four money market spreads that are commonly monitored: the spread between the 3-month London interbank-offered rate (Libor) and the 3-month overnight index swap (OIS) rate; the spread between the rate on a 3-month forward rate agreement (FRA) to begin in 3-months (3x6) and the 3-month OIS rate 3 months forward; the spread between the federal funds rate (FFR) and the overnight Treasury general collateral (GC) repo rate (RP); and the spread between the 3-month Libor and the yield on a 3-month Treasury bill (TB), the so-called TED spread.[1] The series for the FFR, the 3-month Libor, and the 3-month TB yield are available through the Federal Reserve Economic Data (FRED) repository of the Federal Reserve Bank of St. Louis. The 3-month OIS and the 3x6 FRA series are obtained from Bloomberg. The Treasury GC repo rate is calculated as a weighted average rate on overnight repurchase agreements where the underlying collateral is U.S. Treasury securities, and the data are collected by the Federal Reserve Bank of New York (FRBNY) as part of a daily survey of the primary dealers. Our data set consists of weekly observations from January 2, 2002 to July 29, 2015, where the availability of the OIS data determines the beginning of our sample period. Weekly series are obtained as averages of daily series as of each Wednesday. The interest rates are plotted in figure 1 and spreads are shown on figure 2. Table 1 reports descriptive statistics for the spreads. In what follows, we discuss the properties and interpretation of each spread in more detail.[2]

The Libor-OIS spread likely has been one of the most closely watched indicators of funding stress, especially since the onset of the financial crisis in the summer of 2007. Libor is the average interest rate at which banks in London offer Eurodollars and it is a commonly referenced benchmark of the short-term interest rate in the U.S. dollar market.[3] The 3-month OIS rate is

[1] Although the Libor-OIS spread uses the spot OIS rate while 3x6 FRA-OIS relies on the forward OIS rate, we use the same notation for the OIS leg in both cases for simplicity.

[2] See Stigum and Crescenzi (2007) for further information on money market rates and the underlying contracts.

[3] Reports of possible misrepresentation of the Libor by certain banks emerged in 2008, see for example "Study Casts Doubt on Key Rate", *Wall Street Journal*, May 29, 2008. Such banks were later fined for attempting to

the average effective federal funds rate expected over the next 3 months, as reflected in overnight index swaps. In an OIS, a fixed rate is swapped for the geometric average effective federal funds rate over the contract period. The transaction involves only marginal counterparty risk since the principal amount is not exchanged between the parties. Hence, the spread between Libor and the OIS rate serves as a spot measure for both liquidity and credit risk premia. As illustrated in panel A of figure 2, the Libor-OIS spread has generally been narrow and positive, reflecting the small credit and liquidity risk premia inherent in the 3-month Libor. Before mid-2007, the spread had been generally fluctuating around 10 basis points (table 1, first column). However, the average increased to about 90 basis points from mid-2007 to mid-2009 and the spread reached as high as 350 basis points in October 2008 following the Lehman Brothers bankruptcy. Since mid-2009, the end of the Great Recession according to the NBER, the spread has been fluctuating around 19 basis points. Over the entire sample period, the spread averaged 26 basis points, and it has generally been very persistent with a first order autocorrelation coefficient of 0.98.

The FRA-OIS spread can be thought of as the forward equivalent of the spot Libor-OIS spread, as it reflects market expectations for funding conditions in the near future. A FRA is a forward contract that determines the rate of interest between parties to be paid or received on an obligation beginning at a future date. It is an interest rate swap with a single cash flow where the underlying reference rate is the 3-month Libor, so it can also be thought of as the over-the-counter equivalent of a Eurodollar futures contract. FRA transactions are mostly entered as a hedge against future interest rate changes. For example, in a 3x6 FRA, the parties agree to trade a specific amount of 3-month Eurodollars three months hence. At the settlement date, if the market rate is higher than the contract rate, the seller pays the buyer the difference based on the principal, or vice versa if the market rate is lower. Since the principal amount does not change hands, there's very little credit risk in FRA transactions. FRA-OIS is calculated as the spread between the 3x6 FRA rate and the 3-month OIS rate 3-month forward. As expected, the averages of the FRA-OIS spread over the full-sample period and the subsamples is fairly close to those of the Libor-OIS spread (table 1, second column). Moreover, the persistence of the FRA-OIS spread is also similar to the Libor-OIS although it is generally somewhat more volatile.

manipulate the Libor, see for example "EU Fines Financial Institutions Over Fixing Key Benchmarks", *Wall Street Journal*, December 4, 2013. Nonetheless, Kuo et al. (2012) find that Libor survey responses broadly track alternative measures between 2007-2009.

FFR-RP spread is the difference between the federal funds rate and the Treasury GC repo rate. The federal funds market is an interbank, over-the-counter market for reserve balances, with most transactions having an overnight term. The FFR is the average interest rate paid on these unsecured loans of reserve balances held at the Federal Reserve Banks. Prior to the global financial crisis, banks typically had relied on the federal funds market to satisfy reserve requirements and other short-term liquidity needs. The Treasury GC repo rate is the rate on secured overnight lending against collateral issued by the U.S. Treasury. Compared to the federal funds market, the repo market has a wider array of participants since it brings together not only banks, but also money market funds, securities broker-dealers, hedge funds, and other financial institutions as well as nonfinancial corporations.

There exists a strong arbitrage connection between the federal funds market and the repo market. When the RP is greater than FFR, lenders of funds can borrow collateral instead of lending to other banks in the unsecured market. As a result, cash moves from the federal funds market to the repo market, creating downward pressure on the RP rate and pushing the FFR up. However, the arbitrage doesn't work the other way, i.e. when RP is below FFR. Because, investors demand for Treasury collateral cannot be substituted with an uncollateralized loan, keeping the RP usually below the FFR. Therefore, the spread between the unsecured federal funds rate and the overnight secured repo rate serves as a measure of counterparty or credit risk in overnight funding markets. However, the spread between the two rates can be quite volatile over short periods of time due to changes in the demand for and supply of Treasury collateral as well as frictions related to financial reporting dates. Negative spread values have become considerably more common since the FOMC reduced the FFR to its effective lower bound; the spread averaged about 1 basis point since mid-2009 as opposed to about 5 basis points prior to the financial crisis (table 1, third column). Persistence of the FFR-Repo spread is notably lower than that of the other spreads, and it is relatively stable in the subsamples.

Several factors likely contributed to changing dynamics in the federal funds market during the ZLB period. Afonso et al. (2013b) show that federal funds market trading volumes declined significantly after the financial crisis against the backdrop of unprecedented levels of reserves in the banking system and the introduction of interest payments on excess reserves (IOER) by the Federal Reserve. The positive spread between the IOER and the effective FFR as well as increased credit risk aversion by lenders also seem to have contributed to changes in the federal funds market, see Afonso et al. (2013a), Afonso et al. (2011), and Bech and Klee (2011). The changing regulatory environment seems to have played a role as well. For example, anecdotal evidence suggests that leverage ratio constraints under Basel III are the primary reasons behind banks' reluctance to engage in arbitrage trades in the federal funds market.

The Libor-TB spread (also known as the TED spread) is calculated as the difference between the 3-month Libor and the yield on the 3-month Treasury bill.[4] It is a commonly used proxy for risk appetite as it measures the perceived risk in lending to banks relative to investing in risk-free Treasury bills. A rising TED spread may be indicative of a withdrawal of liquidity from funding markets because of an increase in the perceived risk about the health of the banking system. Even though this measure presumably captures risk dynamics similar to the Libor-OIS spread, it also provides useful insights into flight-to-quality dynamics during times of stress since such pressures may manifest themselves in decoupling of returns on Treasury securities from other money market rates. The pre- and post-crisis averages of the TED spread are close at around 25 basis points (table 1, fourth column). Between mid-2007 and mid-2009, values above 150 basis points were common and values as large as 300 basis points were observed in the aftermath of the Lehman Brothers bankruptcy. Persistence characteristics of the TED spread are close to those of the Libor-OIS and the FRA-OIS spreads.

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 an error correction term. This is because the two time series can both be approximated as I(1) processes, and they are not expected to drift away from each other for a prolonged time due to arbitrage and policy intervention.[5] 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,

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

[4] The TED spread used to be calculated as the difference between the 3-month Eurodollars contract and the yield on a 3-month Treasury bill until the Chicago Mercantile Exchange dropped Treasury bill futures following the 1987 crash.

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

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 and its elements are allowed to have non-zero contemporaneous correlation.

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. In practice, the speed of adjustment is more likely to be a function of the magnitude of the spread. As the deviation from the long-run equilibrium becomes larger, so does the profitability of arbitrage or the likelihood of policy intervention, which likely lead to quicker adjustments back to equilibrium.[6] Moreover, the tendency of the system to move toward a long-run equilibrium may not even be present in every time period. Prolonged deviations from long-run average values may hinder adjustment toward equilibrium and result in asymmetric behavior over different time periods.[7] Therefore, we allow for regime-switching in the parameters of the VEC model to allow for discontinuous adjustment to equilibrium as well as other potential asymmetries. We assume that the level of the lagged spread between the two rates, which serves as the error correction term, also determines the regimes characterized by different dynamics.

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

[6] Several studies on the process of price discovery in financial markets, such as e.g. Dwyer et al. (1996), Martens et al. (1998), and Theissen (2012), find evidence of nonlinear adjustment dynamics between spot and futures markets that can be modeled through nonlinear VEC models.

[7] See for example Balke and Fomby (1997) who argue that discrete adjustment processes describe the behavior of many economic phenomena.

of linearity complicate the otherwise standard procedures of Wald or likelihood ratio testing. We follow the recursive residual-based testing method of Tsay (1998) that produces 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 $S = \{s_1, \ldots, s_{T-1}\}$. In particular, we 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), e.g. Gonzalo and Wolf (2005). 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).[8] 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:

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

where $\omega_{i,j} = (1-\alpha_i-\beta_i)\sigma_{i,j}^2$ and $\sigma_{i,j}^2 = E\left[\epsilon_{it}^2 \mid \gamma_{j-1} < s_{t-1} \leq \gamma_j\right]$. 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 four 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.

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

4 Empirical Results

4.1 Testing for Unit Root, Cointegration and Nonlinearity

As in Balke and Fomby (1997) we follow a two-step approach and first test for cointegration between money market rates and then explore potential nonlinearities in their long-run relationship. Table 2 summarizes the results of the unit root tests for the six interest rate series and the four spreads. Test statistics for the rates and spreads are reported in panels A and B, respectively, and the critical values are given in panel C. We report the augmented version of the Dickey and Fuller (1979) test (ADF), GLS-detrended Dickey-Fuller test (DF-GLS), the point optimal test of Elliott et al. (1996) (ERS), the t-type test of Ng and Perron (2001) (NP), and the Phillips and Perron (1988) test (PP). As can be seen from panel A, interest rates are well approximated by I(1) processes over the full-sample since all test statistics agree at typical conventional significance levels that the interest rate processes contain unit roots.[9] The potential cointegrating relationship we focus on crucially depends on the stationarity of the spread between the two interest rate series in each case. Therefore, tests of cointegration boil down to tests of unit root for the spreads. Tests statistics shown in panel B confirm our expectation that each pair is cointegrated over the full-sample period where the corresponding spread serves as an error-correction term.

Table 3 summarizes the results of Tsay (1998)'s threshold nonlinearity test for the null of a linear VEC against the TVEC where the stationary spreads serve as both the error correction terms and the variables driving the regimes. The initial sample size used to start the recursion is $T_0 = \lceil cT^{1/2} \rceil$ where $c = 2$, but qualitatively similar results are obtained with $c \in \{3, 4, 5\}$. In case of a parsimonious first order model ($p = 1$), the null of linearity is strongly rejected for all pairs with the exception of FRA-OIS. This result holds when the lag order is selected under different information criteria (Akaike, Schwarz and Hannan-Quinn).[10] However, we reject the null at 10% significance level in case of the FRA-OIS pair when we choose the lag order with respect to Akaike information criterion as in Tsay (1998).

[9] The KPSS test of Kwiatkowski et al. (1992) that assumes stationarity under the null leads to qualitatively similar results for both the interest rates and the spreads.

[10] We consider the maximum lag order of four because with $p = 4$ the linear VEC has a saturation ratio—the number of data points per parameter—of 71 which decreases to only 24 for the three regime TVEC.

Because the threshold nonlinearity test is not informative about the number of regimes, we mainly rely on information criteria for this purpose, see Tsay (1998) for a similar approach for threshold models and Guidolin and Timmermann (2006) for Markov-Switching models. As can be seen from Table 4, for $p = 1$ all three information criteria favor threshold models over linear models and the three-regime model over the two-regime model for all pairs of interest rates. Additional findings that are not reported here to save space indicate that this result holds for $p > 1$ as well. 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 first-order TVEC models with three regimes. [11]

4.2 Threshold Estimates and Regimes

The threshold estimates and their subsampling-based confidence intervals at 90% level are shown in panel A of table 5. Regime classifications from the TVEC models are plotted in Figures 3 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 be referring to regime-classifications based on the point estimates of the threshold parameters.

For the Libor-OIS spread, the low and high threshold estimates are 40 and 86 basis points, respectively (table 5, panel A). The first regime can be regarded as a state of normal market functioning in which the spread fluctuates at levels not far from the long-run mean. The second regime is characterized by an increase in funding pressures, while in the third regime such pressures reach high levels and market functioning may be substantially impaired. The width of the symmetric confidence band for the low threshold is 20 basis points while that of the high threshold is about 30 basis points. Relatively lower precision in the estimation of the high threshold is likely due to extremely high volatility at the height of the crisis.

As for the dating of the regimes, the first regime had prevailed from the beginning of the sample until August 2007, around the time BNP Paribas announced that it was ceasing activity

[11] Results under higher lag orders yield qualitatively similar results and are available upon request.

in three investment funds specialized in U.S. mortgage debt (figure 3, panel B).[12] This announcement seemed to be an important sign of the propagation of stress related to mortgage backed securities in the broader financial system, and our analysis documents the regime-shift in the money markets around that time. The second regime dominated the period that followed until the widespread turmoil triggered by the Lehman Brothers bankruptcy in September 2008 took place. The spread eventually declined and the system reverted back to the second regime in April 2009 as funding pressures subsided amid various unconventional policy measures undertaken by the Federal Reserve. By mid-2009, the end of the recession according to the NBER, the Libor-OIS spread reached levels consistent with the system being in the first regime. After this point, there were two instances of relatively elevated spreads in the post-crisis period. 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, and breached the estimated threshold in late-2011 amid increased financial distress in Europe due to the sovereign debt crisis. In both of these episodes the Federal Reserve expanded the swap facilities with other major central banks to provide U.S. dollar liquidity to the offshore market, which seemed to help bring the spread back to levels closer to its long-run average.

The FRA-OIS regimes can be interpreted in a similar fashion, i.e. normal, moderate-stress and high-stress regimes. The point estimate for the first threshold is nearly identical to that of Libor-OIS while the second threshold is estimated to be somewhat lower. In part because of this difference, as can be seen from figure 4, the FRA-OIS pair entered the third regime earlier and stayed in that regime longer compared with the Libor-OIS. Another notable difference is that the FRA-OIS spread suggested a movement to the moderate-stress regime both in mid-2010 and late 2011 while the Libor-OIS estimates suggest a regime-shift only in 2011. Both in case of the high stress regime that prevailed during the financial crisis and the moderate stress period associated with the sovereign debt crisis in Europe, the FRA-OIS spread signaled a regime shift earlier than the spot rate based Libor-OIS spread, emphasizing the forward looking nature of the former.

For the FFR-RP pair, the three regimes identified by two threshold estimates have different interpretations than the above described cases. The first threshold estimate is practically zero, so

[12] Prior to this announcement, Standard and Poor's and Moody's had downgraded over 100 bonds backed by subprime mortgages and hedge funds sponsored by Bear Sterns with investments in complex securities backed by subprime mortgages had collapsed.

the first regime is associated with the relatively unusual case of the FFR printing below the RP rate. Although this is typically observed only around financial reporting dates, consistent with the changes in the federal funds market activity discussed above, it became much more common after the reduction of the FFR to its effective lower bound in December 2008. The second threshold estimate of 15 basis points distinguishes times of elevated funding pressures characterized by the widening gap between unsecured and secured rates from times of usual market functioning captured by the intermediate regime. Prior to the crisis, the spread has mostly fluctuated between the two thresholds, with the exception of some short-lived jumps around quarter-end and year-end dates where the FFR remained below the RP rate (figure 4). Most of the crisis period until the beginning of the ZLB period in December 2008 is characterized by the third regime.

Finally, in case of the Libor-TB spread, plotted in figure 6, the threshold estimates, at 53 and 95 basis points respectively, are somewhat higher than the Libor-OIS spreads, likely reflecting the effects of flight to quality flows on short-term Treasury yields. Nonetheless, the resulting regime-classification is similar to the Libor-OIS case. A notable exception is the stress period in late 2011 and early 2012: it is classified in the first regime with respect to the TED spread while Libor-OIS indicates a shift to the intermediate stress regime.

As a robustness check, we also estimated SETAR models for each of the four spreads and compared the threshold estimates with those coming from the TVEC models estimated for pairs of rates. The threshold estimates and the corresponding confidence intervals from the first order SETAR model are reported in panel B of Table 5. Comparison of these values with those reported in panel A reveals that the two estimation methods generally produce very similar point and interval estimates for the spread thresholds, resulting in similar regime classifications. The only notable difference is observed in case of the FRA-OIS spread where the SETAR model produces a somewhat lower point estimate for the first threshold, and as a result, a slightly different regime classification.

4.3 Regime-dependent Equilibrium Dynamics

Tables 6 to 9 report parameter estimates of the T-VEC models for each pair of rates, respectively. In each case, the subscripts 1 and 2 index the essentially risk-free base rate and the relatively risky funding rate, respectively.

Table 6 shows parameter estimates for the Libor-OIS case. The speed of adjustment parameters are negative for both rates and statistically significant in the normal (first) and the high-stress (third) regimes. In these two regimes, when the spread deviates from its long-run average, both rates move in the same direction but the risky rate (the Libor) is more responsive. In terms of economic significance, the magnitude of adjustment appears to be rather small in the first regime. In particular, a 10 basis point deviation of the spread from its long-run mean predicts only 0.2 basis point compression in the spread during the following week as a results of the adjustment in the underlying rates. However, in the third regime, the same amount of deviation from the long-run equilibrium implies an adjustment that is five-times bigger. Our results also suggest presence of an economically meaningful adjustment mechanism in the second regime as well, but the estimates are not significantly different from zero in the statistical sense. Overall, the equilibrium adjustment is both economically and statistically significant only in case of the third regime for the Libor-OIS case. The gradual adjustment in the high-stress state is consistent with combined effects of unconventional policy tools that aimed to reduce risk spreads and response of some market participants to the unusually high levels of compensation for taking on additional risk. In addition, when we estimate a linear VEC model for the Libor-OIS pair, we find that the implied equilibrium dynamics largely coincide with those of the first regime from the nonlinear TVEC model.[13] Hence, the linear model masks the statistically and economically meaningful adjustment in the third-regime following large shocks to the system.

Parameter estimates for the FRA-OIS case are reported in Table 7. The adjustment parameters in the first regime are both statistically significant at 1% level but they have the same sign and magnitude. Thus, an adjustment toward a long-run equilibrium is absent. In contrast, the second regime is associated with an adjustment through changes in the FRA rate significant at 10% level. Specifically, a 10 basis points shock to the spread relative to its long-run average predicts a decline of about 4 basis points in the FRA rate. In the high-stress regime, both rates respond negatively to the error correction term and the implied responses are highly statistically significant. In addition, the estimated adjustment is smaller in the third regime than that in the moderate stress regime. Given a 10 basis points shock to the spread the OIS rate is projected to

[13] To save space we do not report the detailed estimates from the linear VEC model for Libor-OIS and the other pairs. Those results are available upon request.

decline by 2 basis points while the FRA rate is expected to decline twice as much. Similar to the case of Libor-OIS, the linear VEC model yields very different results. It is effectively an average of the three regimes resulting in a statistically significant adjustment that is economically much weaker.

For the FFR-Repo case shown in Table 8, the adjustment parameter in the repo equation is always larger in magnitude, consistent with the monetary policy implementation mechanism. Until late 2008, the effective FFR has been kept near the target rate through open market operations, possibly limiting the adjustment of the federal funds rate in response to movements in the repo market. Moreover, Bech et al. (2014) argue that the secured nature of repo transactions makes participants more willing to exploit pricing anomalies, leading to adjustment to deviations through the repo market, and not the federal funds market. Indeed, the one-way arbitrage between the two markets discussed above (see section 2) is reflected in the coefficient estimates in the first regime where the spreads is negative. Our point estimates suggest an approximately one-to-one adjustment in terms of the total response of the two rates, with the sensitivity of the RP rate being more than twice as large as that of the FFR. However, statistical significance is lacking in the first regime. The second regime, which is characterized with a positive spread smaller than 15 basis points, also lacks in terms of statistical significance of the adjustment mechanism. The adjustment is both economically and statistically significant only in the third regime where the spread exceeds 15 basis points. Several episodes during the crisis period associated with elevated levels of funding stress fall in this category. In this regime, a 10 basis point shock to the spread predicts a 5 basis point rise in the RP rate and a 2 basis point decline in the FFR. In contrast, the linear VEC implies adjustments of similar magnitudes in both rates and attributes a less statistically significant role for the RP adjustments.

Finally, Table 9 reports results for the Libor-TB pair. In the first regime, an economically small adjustment toward the long-run equilibrium takes place via an increase in the TB rate in response to a positive deviation in the spread. Interestingly, once the system enters the second regime, the TB rate is projected to decrease significantly further relative to the Libor suggesting a further rise in the spread. Once the spread is sufficiently high and the system enters the third regime, then a gradual adjustment back toward the long-run equilibrium is projected through decreases in the Libor rate, as in the case of the Libor-OIS pair. The difference between the

Libor-OIS and Libor-TB cases in the moderate stress regime likely reflects the effects of flight-to-quality flows during times of stress on Treasury yields, emphasizing the role of market liquidity risk premium besides the traditional term premia and credit risk effects. As in the case of the Libor-OIS pair, the linear VEC masks such complex dynamics and suggests a statistically significant but economically small average adjustment in response to shocks to the spread.

4.4 Time-varying Volatility and Correlation

Table 10 reports the parameter estimates of the multivariate GARCH models. As before, the subscripts 1 and 2 index the essentially risk-free base rate and the relatively risky funding rate, respectively. In case of the Libor-OIS pair, the risky funding rate (Libor) has a larger reaction parameter (α) in the individual GARCH equation and a slightly lower overall persistence in the volatility process. The regime-dependent volatility drift parameters of the two rates are close to each other in the first two-regimes, with both being larger in the second regime. However, in the third regime, the OIS volatility drift slightly declines relative to the intermediate regime while that for Libor moves up substantially. Indeed, the volatility drift for Libor monotonically increases as a function of the spread. The estimates for regime-dependent volatility drifts for the FRA-OIS case depict a similar picture: the risky rate is subject to a larger jump in volatility when funding stress increases. However, the volatility drifts of the relatively safe rate tend to be larger in case of both FFR-RP and Libor-TB pairs. This pattern is likely driven by the effects of flight-to-quality flows and increased demand for Treasury collateral during times of stress.

Regarding conditional correlations, 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. In case of Libor-OIS, the regime-dependent correlation coefficient declines substantially as the spread breaches the first threshold and then turns negative in the third regime when funding stress reaches its maximum level. The FRA-OIS and Libor-TB cases exhibit a similar pattern across the two regimes. For the FFR-RP pair, the correlation during normal times of market functioning as represented by the second regime is 0.66 and drops slightly when the spread between the two rates increases above 15 basis points, i.e. in the third regime. However, in the first regime, which mostly represents FFR-RP dynamics during part of the ZLB period, the correlation coefficient diminishes substantially to

0.2. This is mainly due to the federal funds rate being almost flat at the zero-lower bound. Although the volatility of the federal funds rate was minimal during the entire ZLB period, the RP rate continued to move with the factors that affect the demand for and supply of cash and Treasury collateral.

All rates exhibit increases in volatilities to unprecedented levels during the financial crisis (figure 7). 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. The volatility of the RP and FFR reverted back to pre-crisis levels at the beginning of 2009 and declined further in mid-2010 amid substantially reduced volume in the federal funds market. Overall, the RP rate has been more volatile than the FFR during the ZLB period as it responds to factors such as the demand for and supply of Treasury securities. Meanwhile, the TB rate volatility reached its highest level during the ZLB period amid the government shutdown in October 2013.

The estimated volatilities of the spreads are plotted in figure 8. Consistent with the volatilities of the rates, level shifts seem to drive most of the crisis period movements and the aforementioned moderate stress episodes during the ZLB period. Since early 2009, spread volatilities generally has been at levels close to or somewhat below their pre-crisis levels. In case of the FRA-OIS spread, the stress in the offshore U.S. dollar funding markets in 2010 and 2011 produced larger and more persistent movements in the estimated volatility series, perhaps reflecting lingering uncertainty about funding conditions in the near-future.

5 Conclusion

We model dynamics of money market rates underlying the commonly-monitored spreads in a threshold-error-correction framework where the spreads serve as both equilibrium correction terms and the threshold variables identifying regimes with different dynamics. We provide estimates and subsampling-based confidence intervals for spread thresholds to quantify funding pressure points from a long-run perspective and identify regimes associated with different levels of funding stress. Our results indicate strong asymmetry in the equilibrium adjustment mechanism in all considered segments of the money market, with cointegrating relationships breaking down in certain regimes. The most economically significant adjustments take place in regimes associated with high risk spreads, likely reflecting a combination of market response to high levels of compensation for additional risk and policy intervention. In addition, allowing for regime-dependent behavior in multivariate GARCH models fitted to the TVEC residuals, we quantify abrupt shifts in interest rate volatilities as well as significant declines in their correlations in high spread regimes characterized by elevated funding stress in money markets.

References

Afonso, G., A. Entz, and E. LeSueur (2013a): "Who's Borrowing in the Fed Funds Market," http://libertystreeteconomics.newyorkfed.org/2013/12/whos-borrowing-in-the-fed-funds-market.html, Liberty Street Economics Blog.

——— (2013b): "Who's Lending in the Fed Funds Market," http://libertystreeteconomics.newyorkfed.org/2013/12/whos-lending-in-the-fed-funds-market.html, Liberty Street Economics Blog.

Afonso, G., A. Kovner, and A. Schoar (2011): "Stressed, Not Frozen: The Federal Funds Market in the Financial Crisis," *Journal of Finance*, 66, 1109–1139.

Balke, N. S. and T. B. Fomby (1997): "Threshold Cointegration," *International Economic Review*, 38, 627–645.

Bech, M. and E. Klee (2011): "The Mechanics of a Graceful Exit: Interest on Reserves and Segmentation in the Federal Funds Market," *Journal of Monetary Economics*, 58, 415–431.

Bech, M., E. Klee, and V. Stebunovs (2014): "Arbitrage, Liquidity and Exit: The Repo and Federal Funds Markets before, during, and Emerging from the Financial Crisis," in *Developments in Macro-Finance Yield Curve Modelling*, ed. by J. S. Chadha, A. C. J. Durré, M. A. S. Joyce, and L. Sarno, Cambridge: Cambridge University Press, 293–325.

Bollerslev, T. (1990): "Modelling the Coherence in Short-run Nominal Exchange Rates: A Multivariate Generalized ARCH Model," *The Review of Economics and Statistics*, 498–505.

Bollerslev, T. and J. M. Wooldridge (1992): "Quasi-maximum Likelihood Estimation and Inference in Dynamic Models with Time-varying Covariances," *Econometric Reviews*, 11, 143–172.

Brunnermeier, M. K. and Y. Sannikov (2014): "A Macroeconomic Model with a Financial Sector," *American Economic Review*, 104, 379–421.

Carlson, M., T. King, and K. Lewis (2011): "Distress in the Financial Sector and Economic Activity," *The B.E. Journal of Economic Analysis & Policy*, 11, 1–31.

Carpenter, S., S. Demiralp, B. Schlusche, and Z. Senyuz (2014): “Measuring Stress in Money Markets: A Dynamic Factor Approach,” *Economics Letters*, 125, 101–106.

Dickey, D. A. and W. A. Fuller (1979): “Distribution of the Estimators for Autoregressive Time Series with A Unit Root,” *Journal of the American statistical association*, 74, 427–431.

Dwyer, G., P. Locke, and W. Yu (1996): “Index Arbitrage and Nonlinear Dynamics between the S&P 500 Futures and Cash,” *Review of Financial Studies*, 9, 301–332.

Elliott, G., T. J. Rothenberg, and J. H. Stock (1996): “Efficient Tests for an Autoregressive Unit Root,” *Econometrica*, 64, 813–836.

Engle, R. (2002): “Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models,” *Journal of Business & Economic Statistics*, 20, 339–350.

Gonzalo, J. and M. Wolf (2005): “Subsampling Inference in Threshold Autoregressive Models,” *Journal of Econometrics*, 127, 201–224.

Guidolin, M. and A. Timmermann (2006): “An Econometric Model of Nonlinear Dynamics in the Joint Distribution of Stock and Bond Returns,” *Journal of Applied Econometrics*, 21, 1–22.

Hakkio, C. S. and W. R. Keeton (2009): “Financial stress: What is it, How can it be Measured, and Why does it Matter?” *Federal Reserve Bank of Kansas City Economic Review*, Second Quarter, 5–50.

He, Z. and A. Krishnamurthy (2012): “A Model of Capital and Crises,” *Review of Economic Studies*, 79, 735–777.

Ivashina, V., D. S. Scharfstein, and J. C. Stein (2015): “Dollar Funding and the Lending Behavior of Global Banks,” *The Quarterly Journal of Economics*, 130, 1241–1281.

Kuo, D., D. Skeie, and J. Vickery (2012): “A Comparison of Libor to Other Measures of Bank Borrowing Costs,” *Mimeo*.

KWIATKOWSKI, D., P. C. PHILLIPS, P. SCHMIDT, AND Y. SHIN (1992): "Testing the Null Hypothesis of Stationarity against the Aalternative of a Unit Root: How Sure are We that Economic Time Series have a Unit Root?" *Journal of econometrics*, 54, 159–178.

MARTENS, M., P. KOFMAN, AND T. C. F. VORST (1998): "A Threshold Error-correction Model for Intraday Futures and Index Returns," *Journal of Applied Econometrics*, 13, 245–263.

NEWEY, W. K. AND K. D. WEST (1987): "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix," *Econometrica*, 703–08.

NG, S. AND P. PERRON (2001): "Lag Length Selection and the Construction of Unit Root Tests with Good Size and Power," *Econometrica*, 69, 1519–1554.

OET, M., R. EIBEN, T. BIANCO, D. GRAMLICH, AND S. ONG (2011): "The Financial Stress Index: Identification of Systemic Risk Conditions," Federal Reserve Bank of Cleveland, Working Paper no. 1130.

PHILLIPS, P. C. AND P. PERRON (1988): "Testing for a Unit Root in Time Series Regression," *Biometrika*, 75, 335–346.

POLITIS, D., J. ROMANO, AND M. WOLF (1999): *Subsampling*, Springer.

STIGUM, M. AND A. CRESCENZI (2007): *Stigum's Money Market*, New York: McGraw-Hill, 4 ed.

THEISSEN, E. (2012): "Price Discovery in Spot and Futures Markets: A reconsideration," *European Journal of Finance*, 18, 969–987.

TSAY, R. S. (1998): "Testing and Modeling Multivariate Threshold Models," *Journal of the American Statistical Association*, 93, 1188–1202.

VAYANOS, D. (2004): "Flight to Quality, Flight to Liquidity, and the Pricing of Risk," NBER Working Paper Series, No. 10327.

Tables and Figures

Table 1: Descriptive Statistics for Money Market Spreads

	Libor-OIS	FRA-OIS	FFR-RP	Libor-TB
	Panel A: January 2, 2002-June 27, 2007			
Mean	11.0	11.2	5.1	26.3
IQR	4.7	6.0	5.6	14.4
AC(1)	0.93	0.94	0.62	0.95
	Panel B: July 3, 2007-June 24, 2009			
Mean	89.9	69.2	19.8	130.6
IQR	36.0	41.4	25.7	58.5
AC(1)	0.95	0.96	0.58	0.92
	Panel C: July 1, 2009-July 29, 2015			
Mean	18.6	22.4	1.3	24.7
IQR	8.1	11.2	4.4	7.7
AC(1)	0.99	0.97	0.73	0.98
	Panel D: January 2, 2002-July 29, 2015			
Mean	25.9	24.7	5.6	40.8
IQR	12.2	14.7	5.4	18.8
AC(1)	0.98	0.98	0.65	0.97

Notes: Data are weekly. Mean and interquartile range (IQR) are reported in basis points. AC(1) denotes first order autocorrelation. FFR is the overnight federal funds rate, FRA is the rate on 3-month/6-month forward rate agreements, Libor is the 3-month London interbank offered rate, OIS is the 3-month overnight index swap rate, RP is is the rate on overnight Treasury general collateral repurchase agreements, and TB is the rate on 3-month Treasury bill the in secondary market.

Table 2: Unit Root Tests

	ADF	DFGLS	NP	PP	ERS
	Panel A: Interest Rates				
OIS	-0.97	-0.93	-0.93	-0.81	11.37
Libor	-0.68	-0.65	-0.66	-0.71	17.66
OIS (forward)	-0.86	-0.78	-0.78	-0.83	14.73
FRA	-0.60	-0.53	-0.53	-0.76	22.13
RP	-1.01	-0.92	-0.95	-0.75	10.67
FFR	-1.31	-1.26	-1.31	-0.80	6.59
TB	-0.60	-0.47	-0.47	-0.75	23.28
	Panel B: Spreads				
Libor-OIS	-3.68	-3.17	-3.21	-2.92	0.96
FRA-OIS	-2.69	-2.65	-2.64	-2.52	1.76
FFR-RP	-5.70	-4.02	-3.98	-12.46	0.46
Libor-TB	-3.14	-2.71	-2.74	-3.12	1.60
	Panel C: Critical Values				
1% c.v.	-3.44	-2.57	-2.58	-3.44	1.99
5% c.v.	-2.87	-1.94	-1.98	-2.87	3.26
10% c.v.	-2.57	-1.62	-1.62	-2.57	4.48

Notes: ADF is the augmented Dickey and Fuller (1979) test statistic, DFGLS is the GLS-detrended Dickey-Fuller test statistic, ERS is the point optimal test statistic of Elliott et al. (1996), NP is the t-type test of Ng and Perron (2001), and PP is the Phillips and Perron (1988) test.

Table 3: Threshold Nonlinearity Tests

	Libor-OIS	FRA-OIS	FFR-RP	Libor-TB
$p = 1$	0.008	0.306	0.000	0.000
$p = \widehat{p}_{AIC}$	0.047	0.097	0.000	0.023
$p = \widehat{p}_{SIC}$	0.047	0.306	0.000	0.001
$p = \widehat{p}_{HQIC}$	0.047	0.306	0.000	0.023

Notes: p-values associated with the threshold nonlinearity test statistics of Tsay (1998) are reported. p denotes the lag order in the linear VEC model assumed under the null. AIC stands for Akaike information criterion, SIC stands for Schwarz information criterion, and HQIC stands for Hannan-Quinn information criterion. Data are weekly and the sample runs from January 2, 2002 to July 29, 2015.

Table 4: Model Selection

	Libor-OIS	FRA-OIS	FFR-RP	Libor-TB
		Akaike		
Linear VEC	-7.1194	-7.1194	-3.7676	-5.1224
2-regime TVEC	-8.2699	-8.2699	-5.0189	-7.5837
3-regime TVEC	-9.5006	-9.5006	-5.8525	-8.2323
		Schwarz		
Linear VEC	-7.0678	-6.4817	-3.7160	-5.0708
2-regime TVEC	-8.2183	-7.1655	-4.9673	-7.5320
3-regime TVEC	-9.4490	-7.5433	-5.8009	-8.1807
		Hannan-Quinn		
Linear VEC	-7.0995	-6.5134	-3.7476	-5.1025
2-regime TVEC	-8.2500	-7.1971	-4.9989	-7.5637
3-regime TVEC	-9.4806	-7.5750	-5.8325	-8.2123

Notes: Model selection criteria for linear and threshold VEC models with $p = 1$ are reported. Data are weekly and the sample runs from January 2, 2002 to July 29, 2015.

Table 5: Threshold Estimates and Subsampling Confidence Intervals

	$CI_L(\gamma_1)$	$\widehat{\gamma}_1$	$CI_U(\gamma_1)$	$CI_L(\gamma_2)$	$\widehat{\gamma}_2$	$CI_U(\gamma_2)$
	Panel A: TVEC Model					
Libor-OIS	30.4	40.0	49.5	70.7	86.3	101.9
FRA-OIS	34.1	41.2	48.4	54.6	63.0	71.3
FFR-RP	-5.1	-0.6	3.9	8.8	15.2	21.6
Libor-TB	43.3	52.6	61.9	75.8	95.2	114.6
	Panel B: SETAR Model					
Libor-OIS	30.1	40.0	49.9	76.5	87.9	99.3
FRA-OIS	18.3	27.0	35.7	54.7	63.0	71.3
FFR-RP	-3.16	-1.6	0.0	7.7	14.2	20.7
Libor-TB	42.8	52.6	62.5	84.1	100.0	115.9

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 January 2, 2002 to July 29, 2015.

Table 6: TVEC Model for Libor and OIS

Parameter	Regime 1	Regime 2	Regime 3
c_1	0.007	-0.030	0.075
	(0.00)	(0.35)	(0.00)
c_2	0.010	0.030	0.208
	(0.00)	(0.38)	(0.03)
a_{11}	0.771	0.549	0.103
	(0.00)	(0.00)	(0.27)
a_{12}	-0.180	0.124	-0.051
	(0.20)	(0.41)	(0.29)
a_{21}	0.513	0.387	-0.520
	(0.01)	(0.01)	(0.29)
a_{22}	0.068	0.595	0.627
	(0.74)	(0.00)	(0.00)
ϕ_1	-0.034	0.025	-0.084
	(0.00)	(0.59)	(0.00)
ϕ_2	-0.052	-0.045	-0.189
	(0.00)	(0.41)	(0.01)

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 2, 2002 to July 29, 2015. Subscript 1 indicates OIS and 2 indicates Libor.

Table 7: TVEC Model for FRA and OIS

Parameter	Regime 1	Regime 2	Regime 3
c_1	0.019	-0.016	0.164
	(0.00)	(0.75)	(0.00)
c_2	0.021	0.179	0.338
	(0.00)	(0.08)	(0.00)
a_{11}	0.231	0.124	-0.012
	(0.21)	(0.29)	(0.94)
a_{12}	0.216	-0.038	0.128
	(0.18)	(0.69)	(0.07)
a_{21}	0.152	-0.079	-0.786
	(0.33)	(0.64)	(0.14)
a_{22}	0.279	0.248	0.438
	(0.07)	(0.06)	(0.04)
ϕ_1	-0.121	0.018	-0.202
	(0.00)	(0.87)	(0.00)
ϕ_2	-0.122	-0.392	-0.407
	(0.00)	(0.07)	(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 2, 2002 to July 29, 2015. Subscript 1 indicates OIS and 2 indicates FRA.

Table 8: TVEC Model for FFR and RP

Parameter	Regime 1	Regime 2	Regime 3
c_1	0.011	-0.001	-0.185
	(0.58)	(0.84)	(0.04)
c_2	-0.006	0.004	-0.009
	(0.59)	(0.24)	(0.84)
a_{11}	-0.434	-0.266	0.302
	(0.16)	(0.11)	(0.01)
a_{12}	1.367	0.166	0.055
	(0.02)	(0.33)	(0.81)
a_{21}	-0.213	-0.024	-0.029
	(0.25)	(0.81)	(0.69)
a_{22}	-0.010	0.003	-0.048
	(0.96)	(0.98)	(0.72)
ϕ_1	0.777	0.187	0.487
	(0.29)	(0.12)	(0.02)
ϕ_2	-0.310	0.045	-0.206
	(0.38)	(0.67)	(0.07)

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 2, 2002 to July 29, 2015. Subscript 1 indicates RP and 2 indicates FFR.

Table 9: TVEC Model for Libor and TB

Parameter	Regime 1	Regime 2	Regime 3
c_1	-0.009	0.246	-0.063
	(0.06)	(0.01)	(0.19)
c_2	-0.002	0.024	0.108
	(0.54)	(0.07)	(0.03)
a_{11}	0.376	1.058	-0.038
	(0.00)	(0.00)	(0.83)
a_{12}	0.170	-1.326	0.199
	(0.04)	(0.04)	(0.11)
a_{21}	0.093	0.212	-0.143
	(0.03)	(0.00)	(0.08)
a_{22}	0.598	0.599	0.716
	(0.00)	(0.00)	(0.00)
ϕ_1	0.040	-0.393	0.023
	(0.05)	(0.00)	(0.36)
ϕ_2	0.014	-0.044	-0.088
	(0.19)	(0.02)	(0.01)

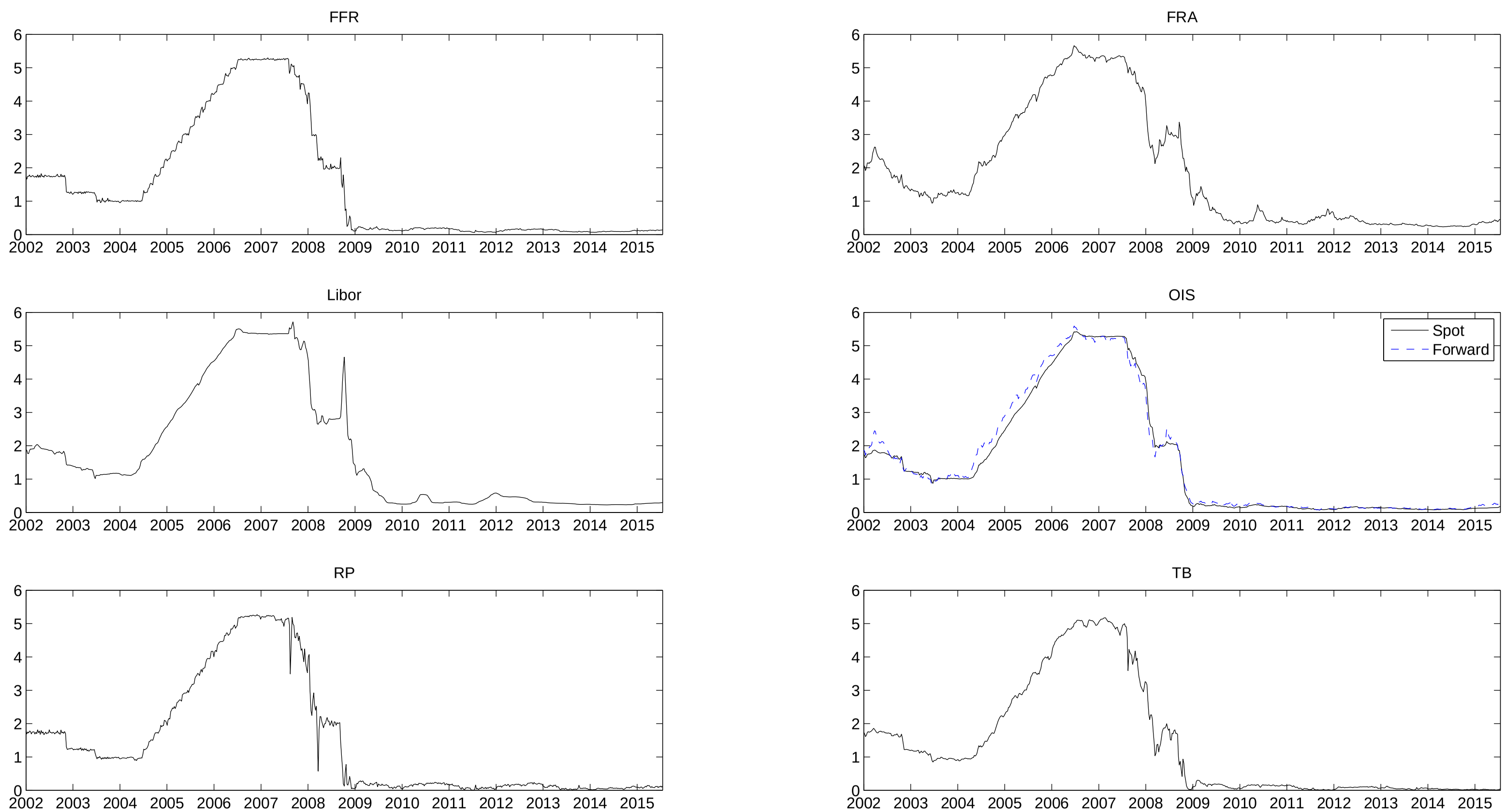
Notes: Parameter estimates and p-values based on Newey and West (1987) HAC standard errors are reported for the three-regime TVEC model. Data are weekly and the sample runs from January 2, 2002 to July 29, 2015. Subscript 1 indicates TB and 2 indicates Libor.

Table 10: Multivariate GARCH Model

	Libor-OIS	FRA-OIS	FFR-RP	Libor-TB
α_1	0.297	0.182	0.159	0.201
	(0.00)	(0.00)	(0.00)	(0.00)
α_2	0.455	0.139	0.197	0.225
	(0.00)	(0.00)	(0.00)	(0.00)
β_1	0.668	0.809	0.830	0.789
	(0.00)	(0.00)	(0.00)	(0.00)
β_2	0.498	0.851	0.793	0.765
	(0.00)	(0.00)	(0.00)	(0.00)
$\sigma_{1,1}$	0.020	0.048	0.120	0.032
$\sigma_{2,1}$	0.019	0.050	0.067	0.019
$\sigma_{1,2}$	0.070	0.060	0.055	0.125
$\sigma_{2,2}$	0.082	0.081	0.049	0.030
$\sigma_{1,3}$	0.050	0.073	0.400	0.194
$\sigma_{2,3}$	0.171	0.128	0.216	0.151
ρ_1	0.495	0.863	0.219	0.228
ρ_2	0.177	0.627	0.656	0.498
ρ_3	-0.177	0.392	0.588	-0.022

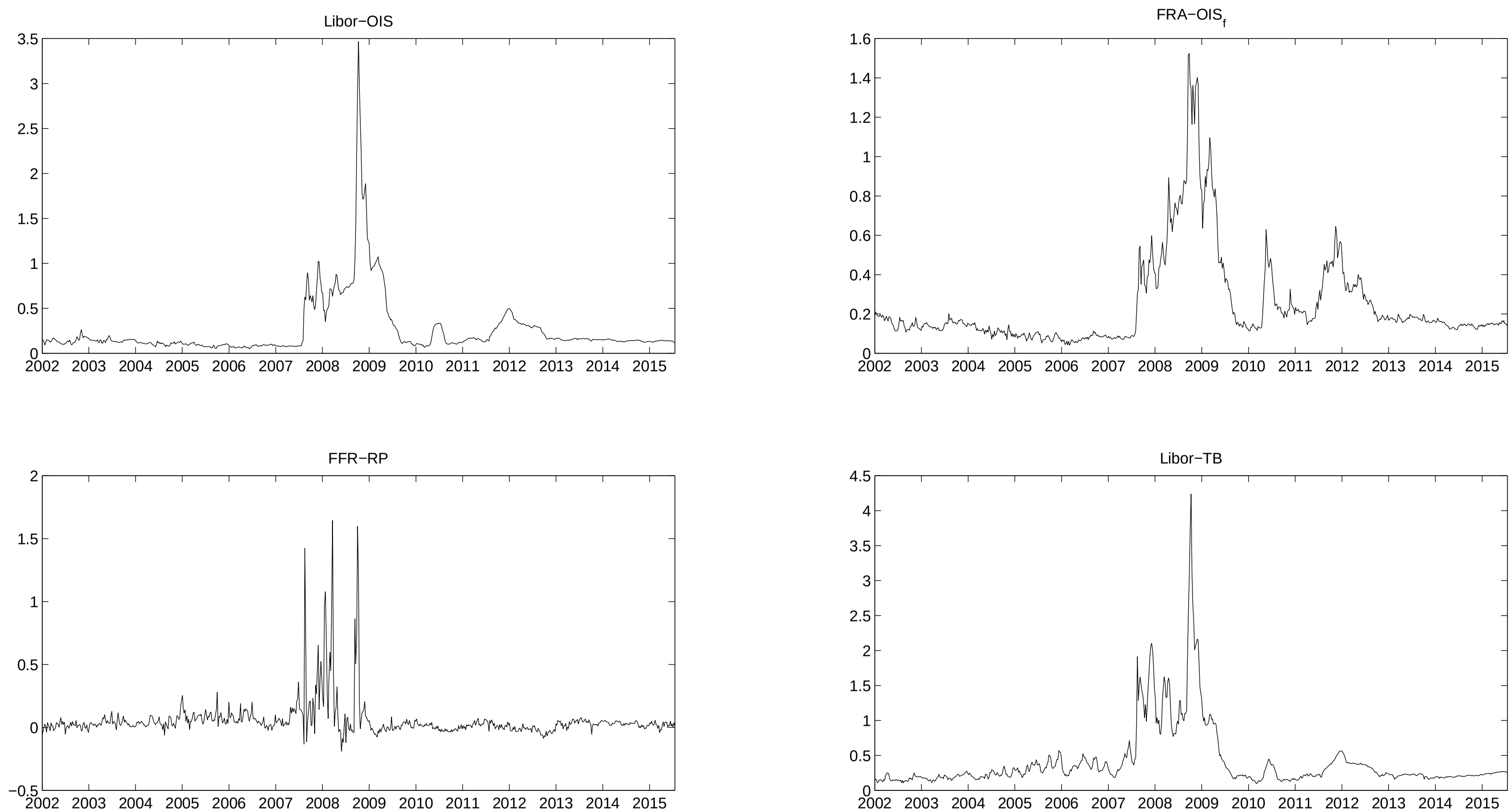
Notes: p-values for GARCH parameters are based on Bollerslev and Wooldridge (1992) robust standard errors. In case of Libor-OIS, subscript 1 indicates OIS and 2 indicates Libor; in case of FRA-OIS, subscript 1 indicates OIS and 2 indicates FRA; in case of FFR-RP, subscript 1 indicates RP and 2 indicates FFR; in case of Libor-TB, subscript 1 indicates TB and 2 indicates Libor. For the regime-switching parameters ($\sigma_{i,j}$ and ρ_j), i indexes rates j indexes regimes. Data are weekly and the sample runs from January 2, 2002 to July 29, 2015.

Figure 1: Money Market Rates



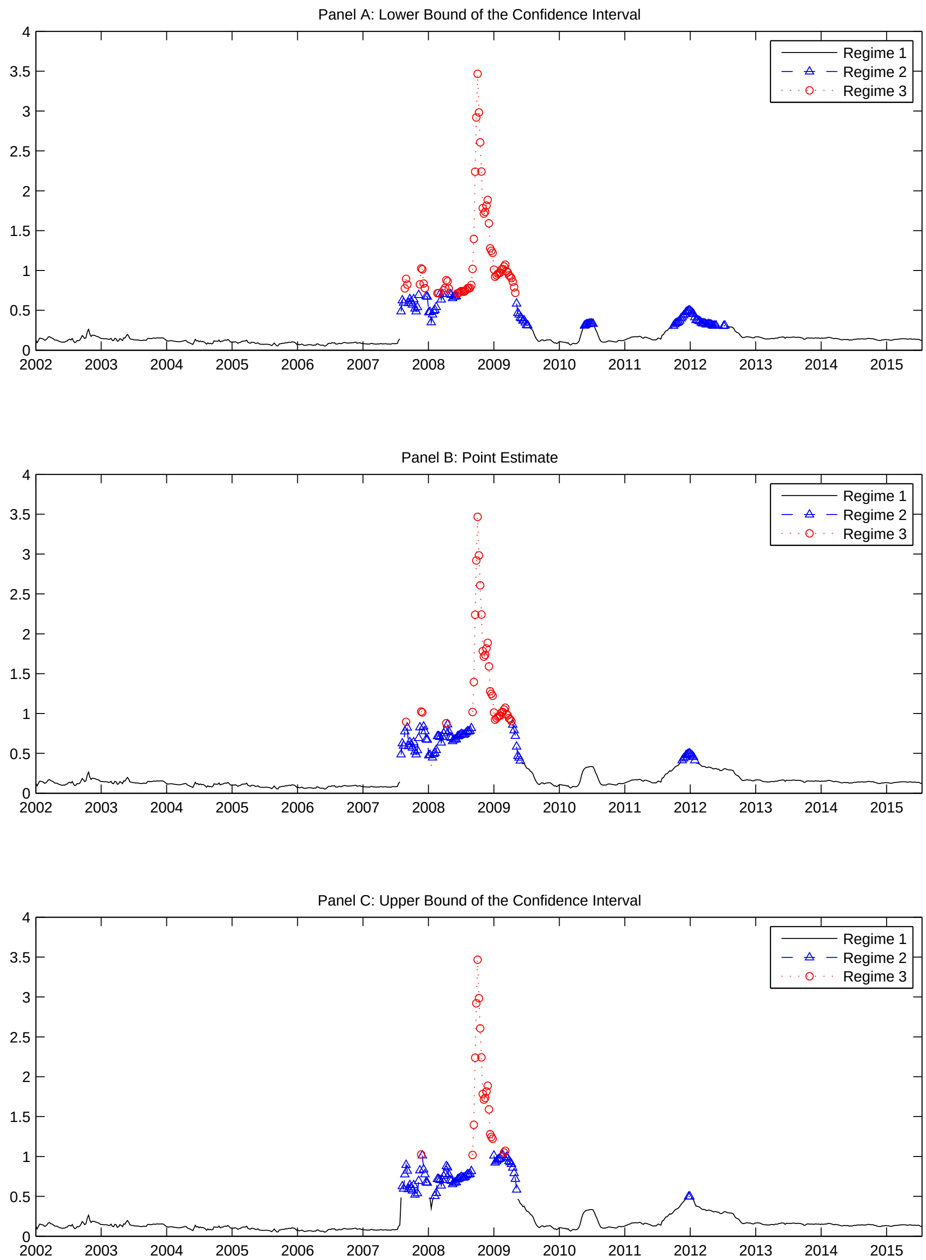
Notes: Data are weekly and the sample runs from January 2, 2002 to July 29, 2015.

Figure 2: Money Market Spreads



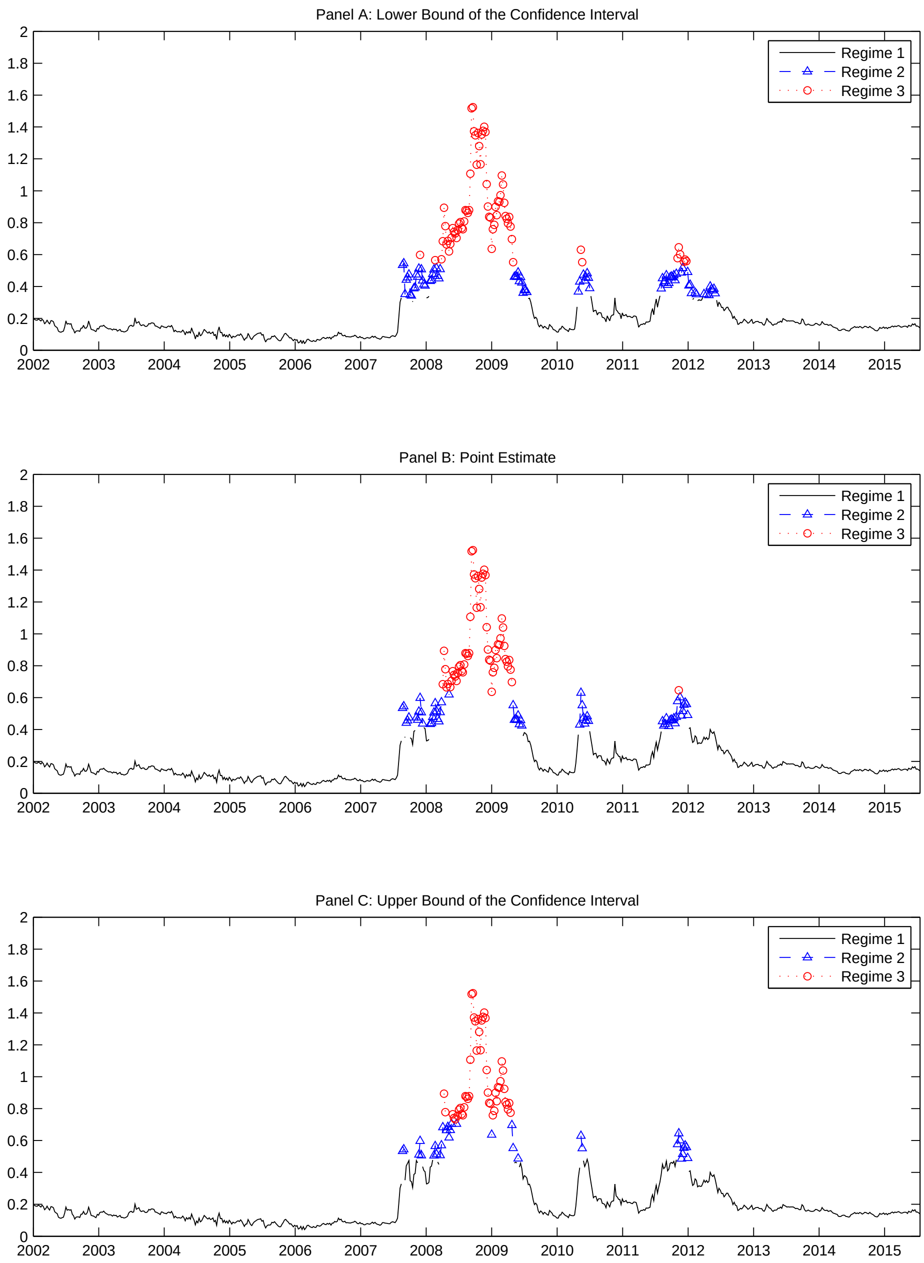
Notes: Data are weekly and the sample runs from January 2, 2002 to July 29, 2015.

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



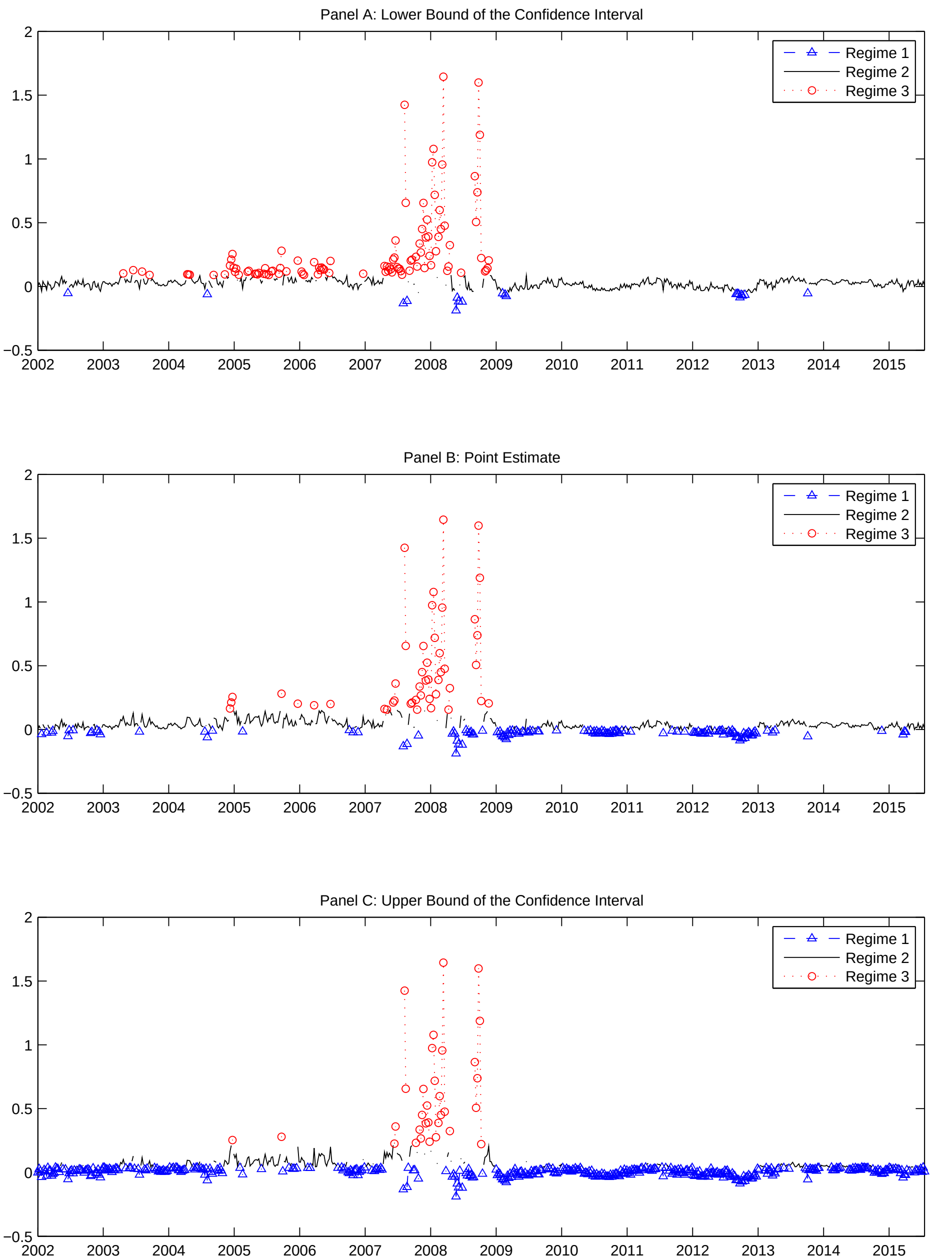
Notes: Data are weekly and the sample runs from January 2, 2002 to July 29, 2015.

Figure 4: Regime Classification from the TVEC Model for FRA-OIS



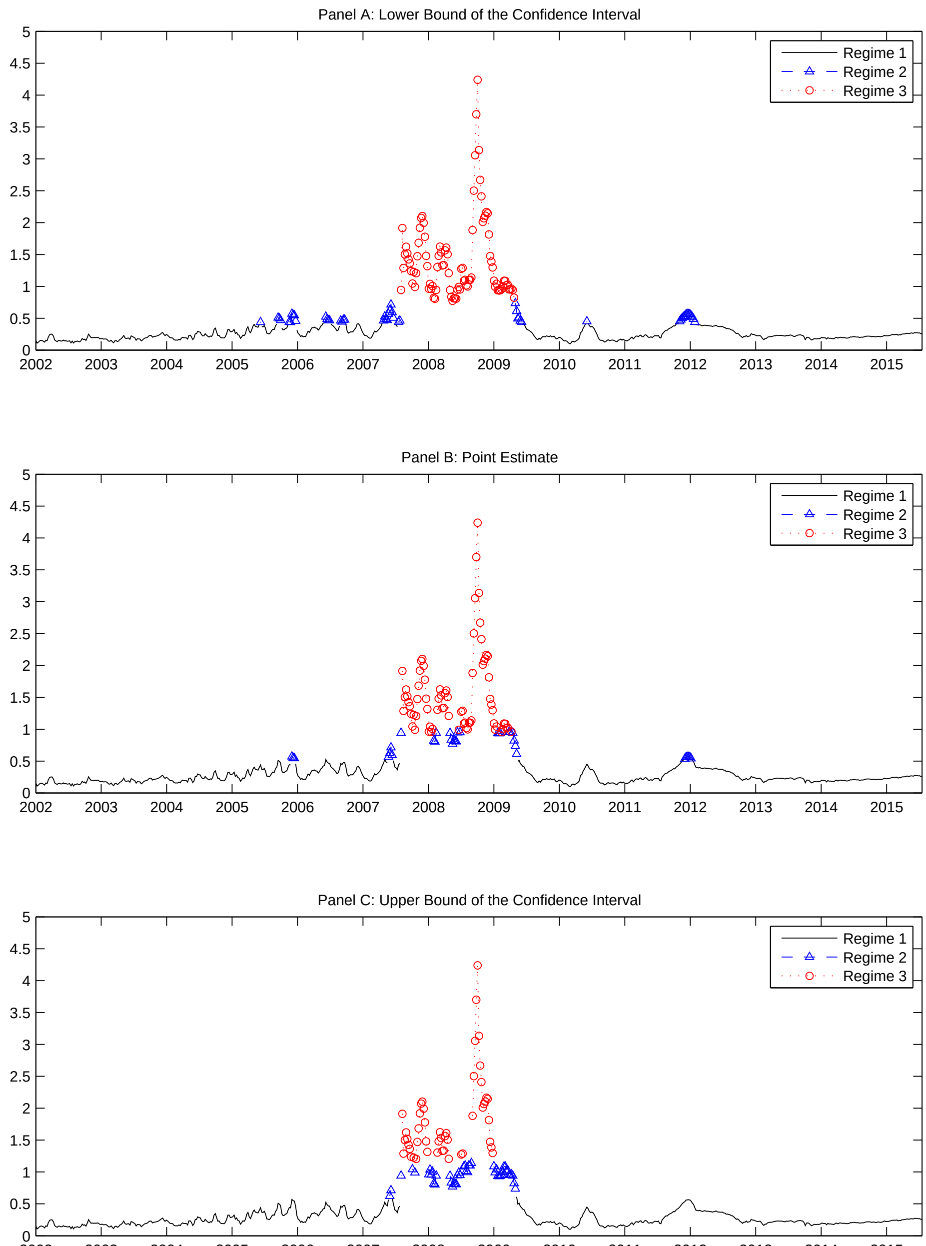
Notes: Data are weekly and the sample runs from January 2, 2002 to July 29, 2015.

Figure 5: Regime Classification from the TVEC Model for FFR-RP



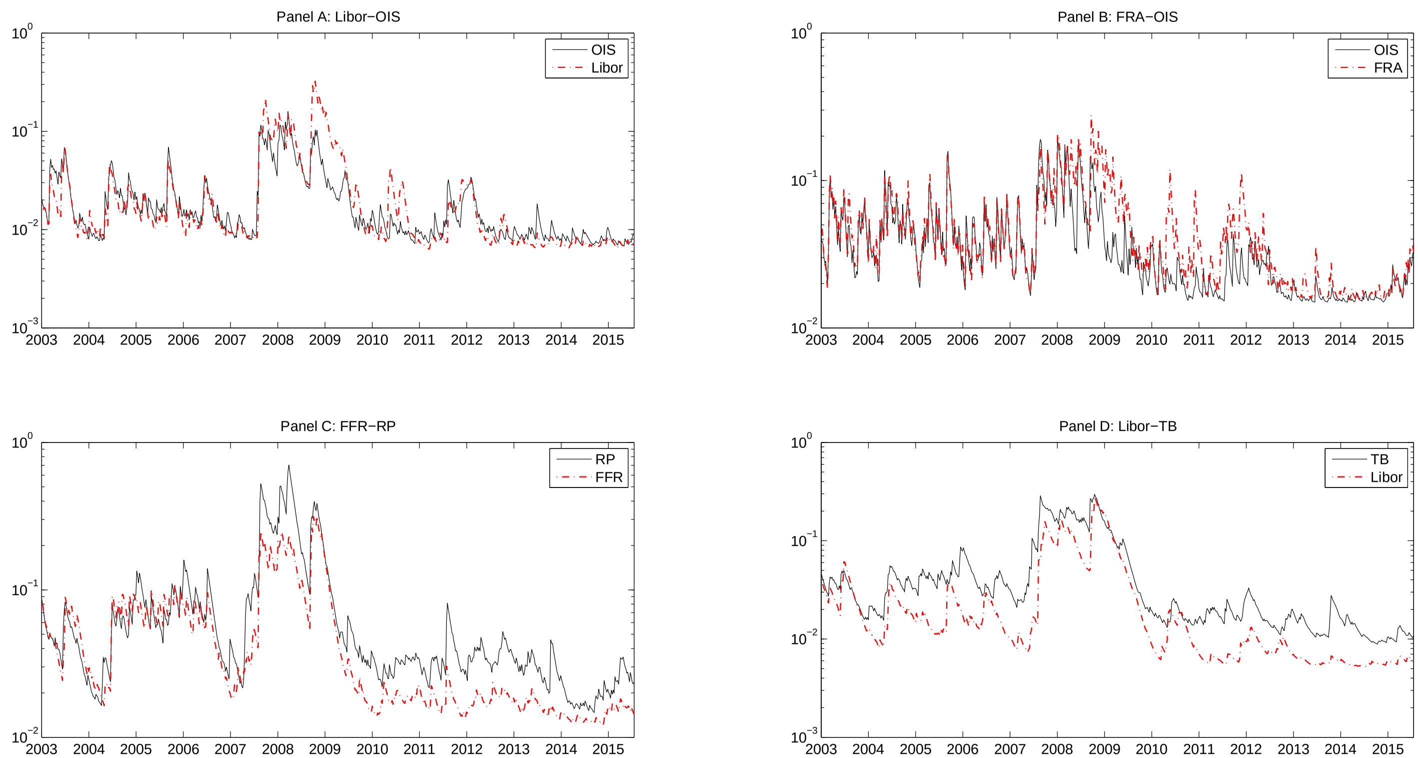
Notes: Data are weekly and the sample runs from January 2, 2002 to July 29, 2015.

Figure 6: Regime Classification from the TVEC Model for Libor-TB



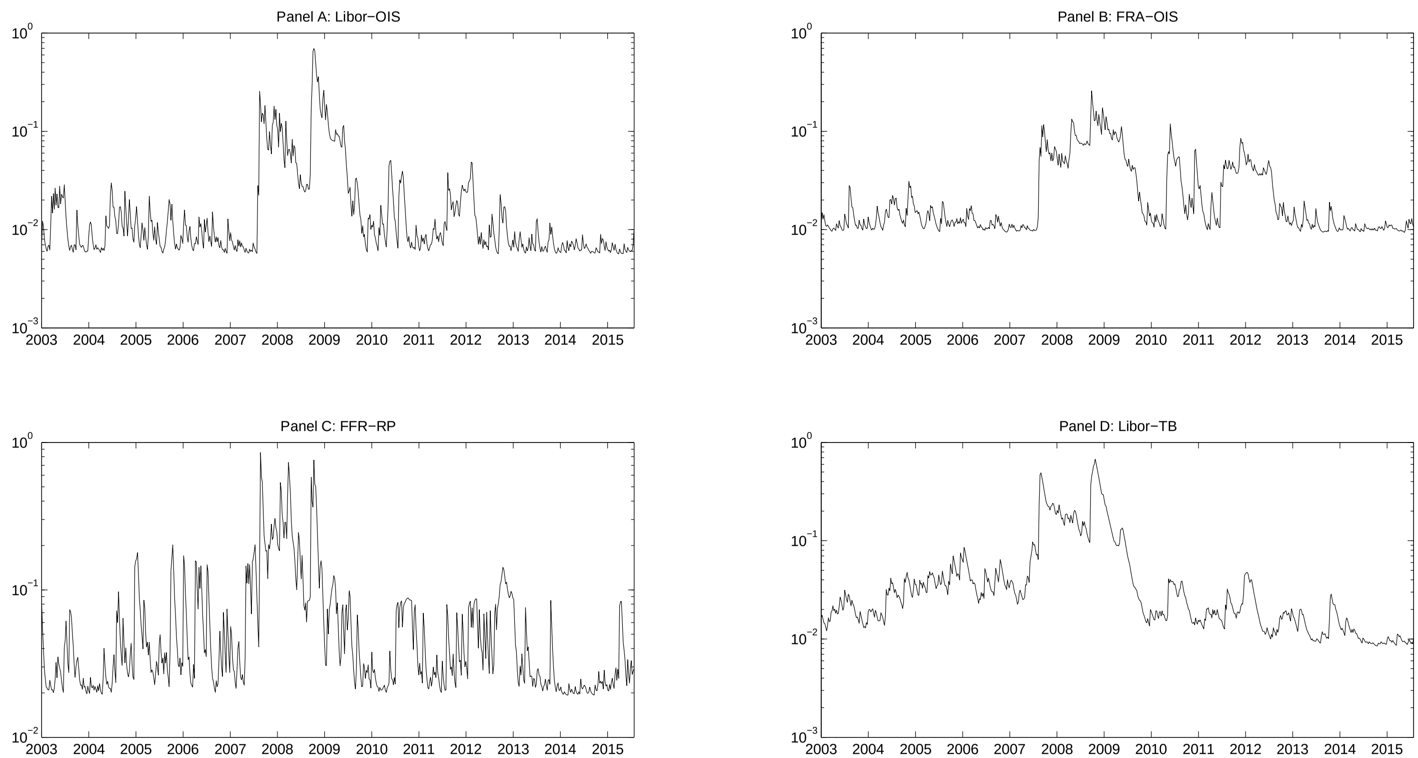
Notes: Data are weekly and the sample runs from January 2, 2002 to July 29, 2015.

Figure 7: Estimated Volatility Series for Interest Rates



Notes: Weekly volatility series are shown from January 15, 2003 to July 29, 2015 on a log-scale. Volatility series are obtained from the multivariate threshold-GARCH model described in the text.

Figure 8: Estimated Volatility Series for Spreads



Notes: Weekly volatility series are shown from January 15, 2003 to July 29, 2015 on a log-scale. Volatility series are obtained from the threshold-GARCH model described in the text.