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Macroeconomic Stress, Equity Market Liquidity Spirals and Markov Regime Switching

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Abstract

This paper makes an attempt to identify the periods of high illiquidity spiral and loss spiral fitting into Markov switching regimes model with Constant Transition Probability and Time-Varying Transition Probability models in US equity market. We identified two different states of the illiquidity spiral and loss spiral in the data associated with the said variables under the CPT and TVTP. However the time-varying transition probabilities for illiquidity spiral and loss spiral have changed significantly during the period under analysis and the explanatory variables are very informative in dating the evolution of the state of the illiquidity spiral and loss spiral over a period of 27 years starting with 1983. Hence TVTP model is preferred over the CTP model in identifying the illiquidity spiral and loss spiral regime switching. In particular, the probability of remaining in the high illiquidity spiral and high loss spiral regimes increases with a decrease in S&P 500 return.

Keywords: Markov regime switching model, constant transition probability, time-varying transition probabilities, liquidity spiral

1. Introduction

Liquidity plays an important role in the well-functioning of the economic system. It is more closely intertwined with the financial markets of the economy (Fuerst, 1992; Brunnermeier, 2008; Naes, Skjeltorp, & Odegaard, 2011). Market liquidity is a function of the information flow (Glosten & Milgrom, 1985; Klibanoff, Lamont, & Wizman, 1998), trading rules (Amihud & Mendelson, 1988), and sentiments of market participants (Baker & Stein, 2004; Chen, Hong, & Stein, 2002). Sudden dry out of the liquidity from the system disrupts business and economic activities in the economy. Brunnermeier and Pedersen's (2009) observe that during 2008 financial crisis liquidity suddenly dried up due to evolvement of liquidity spiral. Some literature suggests that market liquidity dryness occurs due to various triggers such as asset price bubbles (Brunnermeir, 2010), credit bubbles (Kiyotaki & Moore, 1997) and liquidity spirals (Brunnermeier & Pedersen, 2009). Further, Brunnermeier and Oehmke (2012) study points out a severe mismatch between funding structure and potential investment venues dried out liquidity from the market during 2008 financial crisis. Jain, Mishra and McInish (2013) also empirically examine and affirm the existence of liquidity spirals during the financial crisis periods in US market.

Whether the existence of such liquidity spiral phenomenon was only limited to 2008 financial crisis, remains an open question for empirical investigation? This phenomenon might be associated with the other periods of financial crisis as well. Against this backdrop, this study uses the spiral measures proposed in Jain, Mishra and McInish (2013) and examine its applicability to identify illiquidity spiral and loss spiral dynamics across different crisis periods from 1983 to 2010 for S&P 500 constituent stocks using Markov-Switching Regime Models (MSRM).

This study contributes to the existing stock of finance literature in three ways. Firstly, we model the dynamic behavior of spiral measure namely illiquidity spiral and loss spiral and their state dependencies perhaps for first time to the best of our knowledge. Secondly, we also examine whether liquidity spiral measure actually captures the variation in the liquidity states together. Thirdly, the correspondence of illiquidity spiral with the loss spiral during the market stress period extends the scope to empirically examine the dynamic co-movement behavior of these two components of liquidity spiral phenomenon. Nonetheless empirical findings of this study extend support partly towards the proposed theoretical liquidity spiral phenomenon by Brunnermeier and Pedersen's (2009).

The rest of the paper is structured as follows. Section 2 provides review of literature on liquidity and liquidity spirals. Section 3 presents materials and methods. Section 4 outlines the econometric methodology that models the periods of illiquidity and loss across the study period. Section 5 delineates the preliminary and empirical findings of the study. Conclusion and limitations are discussed in section 6.

2. Literature Review

2.1 Liquidity and Liquidity Measure

There is no such unique definition of 'liquidity'. Being multidimensional in nature, it is neither observed nor measured directly (Amihud, 2002). Measurement without definition is, however, difficult if not impossible. Researchers have used different proxies to measure different dimensions of asset liquidity. According to Larry Harris, liquidity has four major dimensions namely, immediacy, width, depth, and resiliency. Immediacy shows how quickly a given size of asset can be arranged, width or market breadth refers to cost involved in trading asset, depth refers to size of asset at a given trading cost and last dimension resiliency indicates how quickly prices revert back to fundamental level. In empirical research, measures the liquidity under a few broad categories (i) volume based measures, which are captured by transaction cost (Stoll, 1978) and market frictions (Stoll, 2000), (ii) price based measure that reflects the resiliency of assets, which is commonly captured by price volatility and market efficiency coefficients (Hasbrouck & Schwartz 1988), and (iii) market impact which indicates the differential impact of liquidity on price (Cvitanić & Malamud, 2011; Ren & Zhong, 2012).

Thus, the finance literature identifies a wide array of proxies for the liquidity measurement, some of them are bid-ask spread, effective spread, trade volume, Amihud illiquidity measure, Roll's estimate, Gibbs sample estimates, Lesmond, Ogden, and Trzcinka (LOT) estimate (1999), and Stambaugh Gamma price impact estimator. However, the usage of such liquidity proxy normally differs based on frequency of data, and richness of data. Despite its importance, problems in measuring and monitoring liquidity risk persist. There are no consensus of using single efficient liquidity measure which captures all the dimensions (Goyenko, Holden, & Trzcinka, 2009; Corwin & Schultz, 2012).

2.2 Liquidity Spiral Phenomenon and Its Measures

Brunnermeier and Pedersen's (2009) theoretical study triggered another debate on the characteristics of liquidity during the severe crisis periods. It is observed that liquidity dynamics and price movement behave in different way and document a reinforcing relationship between illiquidity and price movement. They named such liquidity dynamics as "liquidity spirals". In a study of 2007-2009 crisis period, Hameed, Kang, and Viswanathan (2010) also find the dynamic relationship between sudden liquidity-dry up and the severity of crisis. The liquidity and crisis association becomes more prominent when liquidity is tied up with the funding availability. Rösch and Kaserer (2013) also document the spiral effect between the financial sector's funding liquidity and an asset's market liquidity. This effect is more prominent during the marker downturn periods. As under the uncertain and panic situations the asset funding becomes difficult and in result an increase in liquidity commonality which then leads to market-wide liquidity dry-ups. In order to define the liquidity spiral phenomenon, Jain, Mishra and McInish (2013) proposed measure to capture liquidity spiral phenomenon. The proposed measure includes two proxies called illiquidity spiral and loss spiral. The illiquidity spiral quantifies the intensity of illiquidity whereas loss spiral measure scales the severity of loss due to decline in the stock prices.

3. Materials and Methods

3.1 Data Sources

The study is based on the secondary data which is obtained majorly from the Center for Research in Security Prices (CRSP) database, provided by The University of Chicago where sample stocks related data are restricted to S&P 500 composite index and the daily stock data from January 1983 to December 2010. The each stock specific data obtained from CRSP are daily stock prices, daily high and low price, bid-ask prices, trading volume data, market capitalization, standard industrial classification, ticker symbol and permanent company code.

3.2 Variables Description

3.2.1 Liquidity Spiral Measure

Liquidity spiral is a new phenomenon documented around 2008 financial crisis and not much studied in depth in the finance literature. However, Jain, Mishra, and McInish (2013) study that examines the existence of liquidity spirals in equity market as predicted by Brunnermeier and Pedersen's (2009). Our work follows the liquidity spiral construction methodology of Jain, Mishra, and McInish (2013) and in brief such construction methodology is presented below:

3.2.2 Illiquidity Spiral

The construction of the illiquidity spiral measure is based on two conditions i.e. assigning direction to 'day wise state of the liquidity' and aggregation of the state of the liquidity for two weeks for each stock. In assigning values for the state of the liquidity, following conditions are resorted to: (i) if today's stock spread is simultaneously greater than the previous day's stock spread and benchmark spread , the liquidity is deteriorating for the stock which is captured by assigning '+1' value, (ii) if today's stock spread is simultaneously lesser than the previous day's stock spread and benchmark spread, the liquidity is improving for the stock which is captured by assigning '-1' value and (iii) violation of any of the aforesaid condition, a value '0' is assigned, which indicates the unchanged state of the stock's liquidity. This expression captures the depth of the illiquidity spiral in terms its duration for each individual stock. For example, a value +10 for illiquidity spiral ($S_{spiral10}$) on a given day shows a high level of illiquidity for a stock.

3.2.3 Loss Spiral

The loss spiral measure assumes that higher is the value of loss spiral, higher is deterioration in the price level. The loss spiral measure is based on two conditions i.e. assigning direction to 'day wise state of the stock price' and aggregation of the state of the price changes for two weeks for each stock. In assigning values for the state of the loss, following conditions are resorted to: (i) if today's stock price is simultaneously lesser than the previous day's stock price and benchmark price, this indicate deterioration in the stock price which is captured by assigning '+1' value (ii) if today's stock price is simultaneously greater than the previous day's stock price and benchmark stock price. The price of a stock is improving which is captured by assigning '-1' value and (iii) violation of any of the aforesaid conditions, a value '0' is assigned, which indicates the unchanged state of the stock's price. This measure captures the behavior of the price series over the previous 10 consecutive days. For example a value -10 for loss spiral ($P_{spiral10}$) indicate improvement in stock prices which is a case of a booming market.

3.2.4 Term Spread

It is measured as difference between 10 years Govt. bond rate and 91 days Treasury Bill Rate and market return is measured as S&P500 index return. Various studies (see Hameed, Kang, & Viswanathan, 2010) has shown that market wide illiquidity get reflected as increase in Term spread and decrease in market return.

3.2.5 Market Return

It is computed S&P 500 composite index return.

3.2.6 TED Spread

It is computed as difference between LIBOR and 91 days Treasury Bill Rate. This variable captures short term market liquidity (Note 1).

4. Econometric Methodology

The applications Markov Switching Regime Model (MSRM) proposed by Hamilton (1989) are prominently found in business cycle change detection (see Lam, 1990; Goodwin ,1993; Diebold, Lee, & Weinbach, 1994; Filardo, 1994; Ghysels, 1994; Kim & Yoo, 1995; Filardo & Gordon, 1998; Kim & Nelson, 1998), periodically collapsing bubbles (Hall et al., 1999), interest rate change detection, exchange rate change detection (Hamilton, 1989), real estate speculative bubble detection (Paskelian, Hassan, & Huff, 2011), detecting volatility regimes (Hamilton, 1996; Hamilton & Lin, 1996), bull and bear market detection (Maheu & McCurdy, 2000), equity trading rules (Alexander & Dimitriu, 2005b, 2005e), credit spread (Alexander & Kaeck, 2008) and transmission of liquidity shock (Frank, Hermosillo, & Hesse, 2008). However to the best of our knowledge, the application of MSRM is not found in the liquidity spiral literature. Thus, in this paper we apply MSRM to estimate and identify the dynamic patterns of illiquidity spiral and loss spiral across time periods.

We use two different variants of the MSRM i.e. Constant Transition Probability Model (CTP) and Time-Varying Transition Probability Model (TVTP). We compare the estimated results under CTP and TVTP model. The CTP estimation include an intercept and the three lags of the dependent variable and a random variable with two states, where regression coefficients and the variance of the error terms are all assumed to be state-dependent as per the Markov switching model. Thus, there are only two possible states, only three explanatory variable and that the error process is normally distributed and homoscedastic in each state. The Markov switching model may be written as:

$$Y_t = \alpha_{s_t} + \beta_{s_t} X_t + \varepsilon_{s_t}, \varepsilon_{s_t} \sim N(0, \sigma_{s_t}^2) \tag{1}$$

where latent state variable $s_t \in (1,2)$ that means s_t takes value 1, if state 1 governs at time 't' and s_t takes value 2 if state 2 governs at time 't'.

$$\sigma_{s_t}^2 = \sigma_1^2 + \sigma_2^2 s_t, \sigma_1^2 \rangle 0 \tag{2}$$

The state variable is assumed to follow a first-order Markov chain (eq. 2) where the *transition probabilities* for the two states are assumed to be constant. Denoting by p_{ij} the probability of switching from state i to state j, the matrix of transition probabilities can be written as:

$$p_{ij} = \begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{pmatrix} = \begin{pmatrix} p_{11} & 1 - p_{22} \\ 1 - p_{11} & p_{22} \end{pmatrix} \tag{3}$$

where unconditional probability in regime 1 is stated by p = $\frac{p_{21}}{p_{12} + p_{21}}$. The complete set of model parameters can be summarized from the above model in a vector, θ = (1, 2, 1, 2, σ1, σ2, p11, p22).

The model is estimated using maximum likelihood, where errors are assumed to be normally distributed in each state. The log likelihood function for the purpose is denoted by $\varphi(x, \mu, \sigma^2)$ the normal density function with expectation μ and standard deviation σ:

$$\varphi(x; \mu, \sigma^2) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left[-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2\right] \tag{4}$$

It is very often argued that constant transition probabilities are too restrictive to explain the behavior of financial or economic variables under the examination as they are not allowed to affect transitional probabilities. As explained by Filardo (1994) and Diebold et al. (1999), the Markov switching model with time-varying transition probability (TVTP) has the advantage over the fixed transition probabilities (CTP) in terms of flexibility. It can recognize systematic changes in the transition probabilities before and after turnings points, capture more complex temporal persistence and allow expected duration to vary across time. In this context, economic fundamentals and policy shocks can influence the regime transition probabilities.

To estimate Markov switching model with TVTP, we have followed Diebold et al. (1999). In the process we endogenized probabilities of changes of regime by incorporating economic variables as their determinants. Then, equation (3) becomes:

$$p_{ij} = \begin{pmatrix} p_{11}(Z_{t-1}) & p_{12}(Z_{t-1}) \\ p_{21}(Z_{t-1}) & p_{22}(Z_{t-1}) \end{pmatrix} = \begin{pmatrix} p_{11}(Z_{t-1}) & 1 - p_{22}(Z_{t-1}) \\ 1 - p_{11}(Z_{t-1}) & p_{22}(Z_{t-1}) \end{pmatrix} \tag{5}$$

where, $Z_{t-1} = (1, Z_{1t-1}, Z_{2t-1}, Z_{3t-1}, \ldots, Z_{kt-1},)$ is a set of information variables.

The transition probabilities are modelled as a logistic functional form such as (6):

State (1), *Time* (*t*), *State* (2).

$$\begin{array}{c} State(1) \\ Time(t-1) \\ State(2) \end{array} \begin{bmatrix} p_t^{11} & p_t^{12} = 1 - p_t^{11} \\ P(s_t = 1 \mid s_{t-1} = 1, Z_{t-1}; \beta_0) & P(s_t = 1 \mid s_{t-1} = 1, Z_{t-1}; \beta_0) \\ \frac{\exp(Z'_{t-1}\beta_0)}{1 + \exp(Z'_{t-1}\beta_0)} & \frac{\exp(Z'_{t-1}\beta_0)}{1 + \exp(Z'_{t-1}\beta_0)} \\ p_t^{21} = 1 - p_t^{22} & p_t^{22} \\ P(s_t = 2 \mid s_{t-1} = 1, Z_{t-1}; \beta_1) & P(s_t = 3 \mid s_{t-1} = 2, Z_{t-1}; \beta_1) \\ \frac{\exp(Z'_{t-1}\beta_0)}{1 + \exp(Z'_{t-1}\beta_0)} & \frac{\exp(Z'_{t-1}\beta_0)}{1 + \exp(Z'_{t-1}\beta_0)} \end{bmatrix} \tag{6}$$

To estimate this regime switching model, we must specify the complete data likelihood function. Following Diebold et al. (1999), let y_t be the sample path of a time series conditional upon as follows:

$$(y_t \mid s_t = i, \alpha_i)^{iid} \sim N(\mu, \sigma_i^2) \tag{7}$$

Where $\alpha_i = (\mu, \sigma_i^2)$ and i=0, 1.

Thus the conditional density function of y_t is specified as:

$$\mathrm{f}(y_t \mid s_t = i, \alpha_i) = \frac{1}{\sqrt{2\pi}\sigma_i} \exp\left[-\frac{1}{2}\left(\frac{y_t - \mu_i}{\sigma_i} \right)^2 \right] \quad (8)$$

where i=0, 1.

Following Diebold et al. (1999), the MSRM TVTP parameters includes the mean and variances of each state (μ, σ_i^2) ∀i=1, 2 the transition probabilities (p_t^{11}, p_t^{22}), their determinants (*β*) and the initial conditions (ρ) are jointly estimated with Maximum Likelihood methods.

Thus, contextualizing equation (1) the illiquidity (Y_t) depends on X_t, its own lags (Y_{t-i}) and σ_t a random variable with iid that follows a normal distribution with zero mean and $\sigma_{s_t}^2$ state-dependent variance in equations (1) and (2). $\alpha_{s_t}, \beta_{s_t}$ in equation (1) determines the behavior of the switching from one state to other under CTP. Equation (3), we specify that the switching of regimes follows a first-order Markov chain, where probabilities are noted by p_{11} and p_{22}, where p_{11} is the probability of remaining in state 1 at *t,* given that the economy is in regime 1 at *t-1*, and p_{22} is the probability of staying in regime 2 at *t,* given that the economy is in state 2 at *t-1*; *1-* p_{11} and *1-* p_{22} are the transition probabilities for switching from one regime to the other under CTP. The maximum log likelihood function is specified in equation (4), which is deployed in estimating the MSRM with CTP. In equation (5) we specify the MSRM with TVTP. Equation (6) is the mathematical representation of the transitional probabilities under MSRM with TVTP. Equation (7) and (8) represent the complete data likelihood function and conditional density function under MSRM with TVTP respectively.

5. Findings

5.1 Preliminary Findings

The summary statistics for major variables used in the study including two spiral measures for full panel period consisting 476 common stocks that are included in the S&P 500 index for the study period is presented in Table 1. Total number of filtered stock sample contains 1,704,907 observations for stock prices. The minimum value of stock price is \$0.35, average value is \$44.81 while maximum value is \$996.74.

We computed relative quoted spread (spread), mid-quote, illiquidity spiral and loss spiral as defined in previous sections. In data sample, the mean value of ask and bid price for stocks is \$44.91 and \$44.7 respectively. Ask and bid price series also show a high kurtosis which indicate variability in the sample. The average high and low trade price is \$44.81 and \$44.01 respectively. The trade volume shows a high variability in sample. The average value of trade volume is 3,554,600 and minimum value is 100. The volume series shows a very high kurtosis 2839.54 and skewness 40.67. Our sample contains constituent of S&P 500 index where there is remarkable variation in stock's market capitalization. Data descriptive also points this variation where minimum market capitalization of a firm is \$16.2 millions and maximum is \$6.14billions. The computed spread value varies from minimum of 0.002 % points to maximum of 196.04%. The spread variable is highly asymmetric in nature with kurtosis value 2476.53. Our main interest variables-loss and illiquidity spirals, value moves in the range of -10 to +10. The average value of illiquidity and loss spiral is -1.08 and -0.58 respectively. However, the skewness and kurtosis value are also not very high for our main interest variables.

Table 1. Descriptive statistics on full sample

Variables	Mean	Std.	Skew.	Kurt.	Min.	Max.	Median
Trade Price (\$)	44.81	40.97	9.3103	138.55	0.35	996.74	38.29
Spread (%)	0.59	0.94	16.252	2476.53	0.002	196.04	0.18
Ask Price (\$)	44.91	41.02	9.3145	138.60	0.35	996.77	38.40
Bid Price (\$)	44.70	40.91	9.306	138.53	0.34	994.54	38.19
Volume(in '000)	3554.60	14699.30	40.666	2839.54	0.10	1897900	1078
Market Cap. ('000) (\$)	18,041,158	38,247,995	5.5241	41.12	16,219	614,687,978	6,726,331
Mid Quote (\$)	44.80	40.97	9.3096	138.54	0.35	995.66	38.30
Illiquidity Spiral	-1.08	3.15	0.273	-0.64	-10	9	-1
Loss Spiral	-0.58	4.70	0.1857	-1.4	-10	10	-1

Note. Total number of observation during the sample period for each variable is 1,704,907.

We provide a plot of estimated variation in illiquidity spiral and loss spiral Figure 1. The series are graphed over the time period 1983 to 2010. It is revealed that the variation in illiquidity and Loss spirals have gone up across the macroeconomic crises periods. The average spread has also gone high during the same period which indicates that the market has become very illiquid in market downturn periods. Further the variation in illiquidity spiral fluctuates more wildly than does loss spiral and both series generally share the same pattern at least around the recessionary periods. For example, the spirals measures magnitude spiking up around the economic crisis of 1987, 2002 and 2008 and it is either spiking down or stabilizing during the rest of the study period (Figure 1).

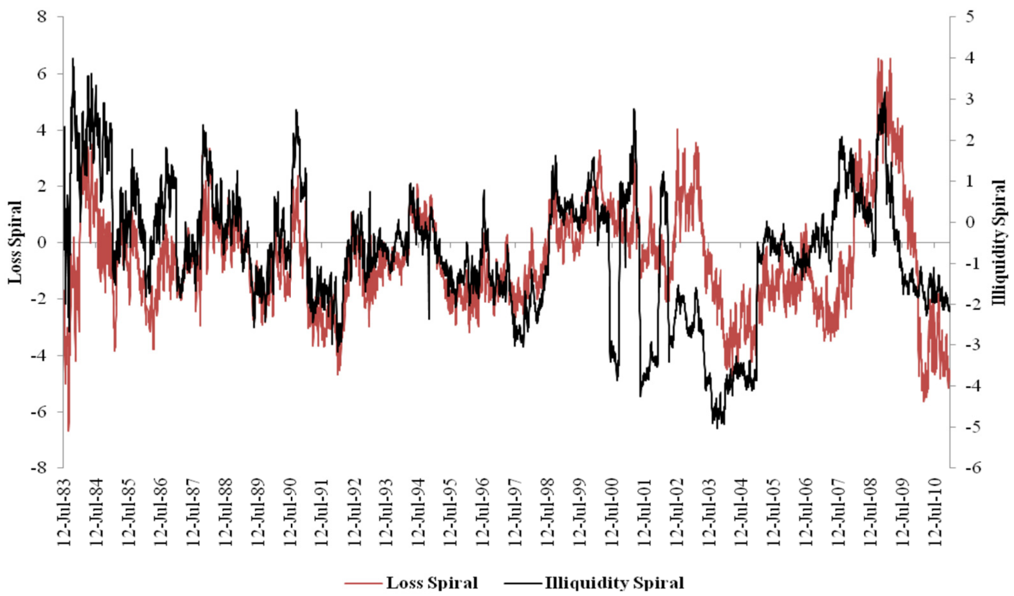


Figure 1. Average daily variation in loss spiral and illiquidity spiral

5.2 Empirical Findings

In this study, we model liquidity spiral measures i.e. illiquidity spiral and loss spiral, independently with the MSRM CTP followed by the MSRM with TVTP. In the MSRM TVTP we examine the switching of regimes by incorporating broad market based financial variables (i.e. term spread and market return) as the determinants of illiquidity spiral and loss spiral. The term spread is used here as a proxy for market liquidity risk as the risk of the market increases at the time of market down turn and decreases at the time of market up turn. The availability of funds may not be even available to a solvent agent at the former market scenario, but it is of limited relevance during times of tranquility or market up turn, where financial intermediaries in many a times does not examine the credit worthiness of the agent and extend the credit. Secondly, the equity market return is used as a proxy for market state, where market return is sensibly low and negative at the time of downturn as compared to a reverse scenario of market up turn. The estimated results from MSRM CTP and TVTP for both the interest variables are presented sequentially.

5.2.1 Illiquidity Spiral and Loss Spiral under CPT

In the first step, we considered explanatory variables (X_t) to be confirmed by an intercept (α_{st}), first three lags of the dependent variable (Y_{t-1}, Y_{t-2}, Y_{t-3}) and the random variable ε_{st} (equation 1).We have built MSRM CTP both for Illiquidity spiral and loss spiral. Hence, our dependent variable for the first model is considered as Illiquidity spiral and for the second is loss spiral. The estimation of the CPT for both illiquidity spiral and loss spiral revealed that none of the autoregressive coefficients found to be statistically significant. Thus, we seek to explore if regime dependence is relevant only to constant and variance and covariance matrix. Against this backdrop, we proceed to estimate the Markov Regime Switching CPT including intercept only both for illiquidity spiral and loss spiral.

The results from estimating first order MRSM CTP have several interesting findings which are reported in Table 2. The maximum likelihood estimates of the parameters in the selected models are found to be statistically significant for both the models at least at the 5% level of significance. The estimated parameters and the LR statistics for illiquidity spiral and loss spiral are observed to be 9884.92 and 11068.92 respectively, which suggest the rejection of the null hypotheses of no regime switching against alternative of regime switching for both the variables. Thus, the estimated results support the assumption that the two different states occurred in the data α_{st} for state 1 and state 2 are statistically different in both the models. In particular, the estimated results suggest that an average increase in illiquidity spiral and decrease in loss spiral of 0.273 and -2.074 unit in bear market regime (intense illiquidity and loss state) and decrease illiquidity spiral (increase in liquidity) of -2.188 unit and increase loss spiral of 0.798 unit in bull market regime(intense liquidity and profit spiral state) respectively. Further the relatively large posterior standard deviation, which is inferred from the variance of the parameter of the state of the illiquidity and loss spiral both reflect that there are a few observations in that state.

While examining the transition probability matrix (TMP) and the expected durations of the both the states it is affirmed that there is considerable state dependence in the transition probabilities with a relatively higher probability of remaining in the origin regime for illiquidity spiral and alternate regime for loss spiral switching regressions. The closer examination of the constant transition probabilities affirm on the one hand that the probability of staying in liquidity spiral state (p11) at time (t), given that the market is in the same state at time (t-1) is 0.9935. On the other hand, the probability of staying in illiquidity spiral states (p22) in time (t), given that the market is in the same state at time (t-1) is found to be 0.9996. Similarly examining the probabilities of remaining in the loss spiral state and non-loss spiral state are affirmed to be very high with a tune of 0.9909 and 0.9912 respectively. The transition probabilities results are observed to be very large and statistically significant at 1% in both the states for illiquidity spiral (p11 = 0.9935 and p22 = 0.9964) which suggest that both states (illiquid and liquid spiral) are highly persistent. It is also further evident for the loss spiral that the state transition probabilities are found to be very large and statistically significant 1%, (p11 = 0.9909 and p22 = 0.9912) which suggests that both the states (loss spiral and non-loss spiral) are highly persistent (Table 2). These high probabilities either in liquidity or illiquidity spiral state and either in loss spiral or non-loss spiral state correspond that it is likely to be in such regimes. Thus the analysis here suggests that the periods can be easily identified under two states both for illiquidity spiral and loss spiral in the US equity market under the study period.

Table 2. Maximum likelihood parameter estimates and standard errors of the first order two state Markov regime switching CPT model for illiquidity and loss spiral

Parameters	Illiquidity Spiral			Loss Spiral		
	Coefficients	SE	Z statistic	Coefficients	SE	Z statistic
αst in state 1	-2.188**	0.0223	98.09	0.798**	0.0321	26.623
αst in state 2	0.273**	0.0172	15.85	-2.074**	0.0246	-83.07
αst in state 1 (σ_1)	0.0339*	0.0121	2.81	0.275**	0.0124	22.26
αst in state 2 (σ_2)	-0.027**	0.0097	-2.78	0.027*	0.0131	2.02
TMP (P11)	5.027**	0.2378	21.03	4.685**	0.1902	24.71
TMP (P21)	-5.401**	0.2393	-22.57	-4.719**	0.1933	-24.52
Parameters			State Dep. Value			State Dep. Value
CTP P11			0.9935			0.9909
CTP P12			0.0065			0.0092
CTP P21			0.0045			0.0088
CTP P22			0.9964			0.9912
Duration	State 1		153.873	Duration	State 1	109.2884
Duration	State 2		222.692	Duration	State 2	113.109
AIC			2.861	AIC		3.2
BIC			2.868	BIC		3.21
Log Likelihood			-9884.92	Log Likelihood		-11068.9
Convergence	Iterations		21	Convergence	Iterations	6

Note. TMP stands for Transaction Matrix parameter, CTP Constant Transition Probability.

**Indicates at 1% level of significance, * indicates at 5% level of significance.

Further an attempt has been made hereunder to conduct the horizontal switching and the duration analysis for the illiquidity spiral and loss spiral in US equity market. It is observed that the probability of switching from a liquid spiral state to illiquid spiral state (P_{12}) is almost 0.0065 and the probability of changing from illiquidity spiral state to liquidity spiral state (P_{21}) is close to 0.0045. The corresponding expected durations to be in illiquidity spiral and liquidity spiral regimes are approximately 222.692 and 153.873 periods respectively. While the probability of switching from the loss spiral state to non-loss state (P_{12}) is almost 0.0092 and the probability of changing from non-loss spiral state to loss spiral state (P_{21}) is close to 0.0088. The corresponding expected duration to be in loss spiral state regime and non-loss spiral regimes are approximately 109.3 and 113.2 respectively (Table 2). However, it is evident that the illiquidity spiral duration is relatively observed to be longer than that of the liquidity spiral duration and the loss spiral duration is shorter than the non-loss spiral duration in the US equity market during our sample study period. Thus it is affirmed that the change from illiquidity and non-loss spiral state to liquidity and loss spiral state is more likely than change from liquidity and loss spiral state to illiquidity and non-loss spiral state in the US equity market.

It can be inferred from the above analysis that relatively illiquidity spiral state is longer than that of the loss spiral state, which corresponds that there might have some stretch of periods either in the state 1 or state 2 where illiquidity spiral and loss spiral don't move together in the US equity market. This non occurrence of simultaneous illiquidity spiral and loss spiral in certain cases of the both the states would be partially examined graphically in filtered and smoothened regime probabilities obtained from both the illiquidity and loss spiral Markov Regime Switching CTP models.

5.2.2 Illiquid Spiral and Loss Spiral under TVTP

We estimate the Markov Regime Switching TVTP both for illiquidity spiral and loss spiral, where we allowed a set of broad financial market variables to explain the evolution of such probabilities. The initial set of proxies used as explanatory variables Markov Regime switching TVTP frameworks selected are broad equity market return (S&P 500 index return), Term spread and TED Spread. With this information we established different models to select the one that presents the smooth transition probabilities consistent with the state of upturn and down turn of the US equity market history since 1983.

Table 3. Maximum likelihood parameter estimates and standard errors of the first order two states Markov regime switching *TVTP* model for illiquidity spiral and loss spiral

Parameters	Illiquidity Spiral			Loss Spiral		
	Estimates	SE	Z statistic	Estimates	SE	Z statistic
αst in state 1	0.268**	0.0175	15.36	1.129**	0.0281	40.23
αst in state 2	-2.195**	0.0220	-100.17	-1.812**	0.0217	-83.53
αst in state 1 (σ_1)	0.948**	0.0170	55.76	1.731**	0.0270	64.11
αst in state 2 (σ_2)	1.026**	0.0370	27.73	1.048**	0.0250	41.57
TMP (P11)	5.463**	0.2561	21.26	4.618**	0.2060	22.44
P11-S&P_{500}RET	-0.229	0.2340	-0.98	-0.145	0.1276	-1.13
TMP (P21)	-5.080**	0.2462	-20.62	-5.391**	0.2660	-20.27
P21-S& P_{500}RET	-0.331*	0.1683	-1.97	-0.904**	0.1923	-4.70
Parameters			State Dep. Values			State Dep. Values
TVTPP11			0.9960			0.990
TVTPP12			0.0044			0.009
TVTP P21			0.0068			0.009
TVTP P22			0.9933			0.991
Duration	State 1		218.58	Duration	State 1	109.78
Duration	State 2		149.75	Duration	State 2	78.22
AIC			2.862675			3.216792
BIC			2.69603			3.22372
Log Likelihood			-9886.40			-11068.93
Convergence	Iterations		23			15

Note. TMP stands for Transaction Matrix parameter, TVTP: Time Varying Transition Probability.

**Indicates at 1% level of significance, * indicates at 5% level of significance.

Table 3 presents the results of the final selected model, which includes only S&P 500 return as explanatory variable in the TVTP model both for Illiquidity spiral and loss spiral. As expected, the external shocks have significantly affected the evolution of both illiquidity spiral and loss spiral in the US equity market. The model was selected based on the gradients and on a likelihood test that compares the Hamilton model, with CTP, with the model of TVTP.

The estimated results of the TVTP model indicate that the US equity market experiences two different states both in the context of illiquidity spiral and loss spiral. The magnitudes of the illiquidity spiral and loss spiral states significantly differ from the liquidity spiral state and non loss state. The illiquidity spiral and loss spiral states are identified with a positive mean value of 0.268 and 1.129 and the liquidity spiral and non loss spiral states are identified with a negative mean value of -2.196 and -1.812 respectively. However on the one hand TVTP and CTP models remained equally efficient in estimating the coefficients for illiquidity spiral under two different regimes and on the other hand TVTP model better discriminates compare to the CTP in segmenting the loss spiral under two different regimes.

Further the coefficients of the S&P 500 return in the TVTP model both for illiquidity spiral and loss spiral differ from zero with opposite (statistically significant) signs under the two different states. As to the transition matrix parameters, we find that increases in the illiquidity are associated with higher probabilities of being in the illiquidity spiral regime, lowering the transition probability out of regime 1 and increasing the transition probability from regime 2 into regime 1. Similarly, the transition matrix parameters, we see that increases in the loss are associated with higher probabilities of being in the loss spiral regime, lowering the transition probability out of regime 1 and increasing the transition probability from regime 2 into regime 1 (Table 3).

While examining the transition probability matrix and the expected durations of the TVTP model it is affirmed that there is considerable state dependence in the transition probabilities with a relatively higher probability of remaining in the origin regime both for illiquidity and liquidity spiral state and loss and non loss spiral states. The corresponding expected duration of illiquidity and liquidity regimes are approximately 218.58 and 149.75 periods and expected duration of loss and non loss regimes are approximately 109.78 and 78.22 periods respectively (Table 3).

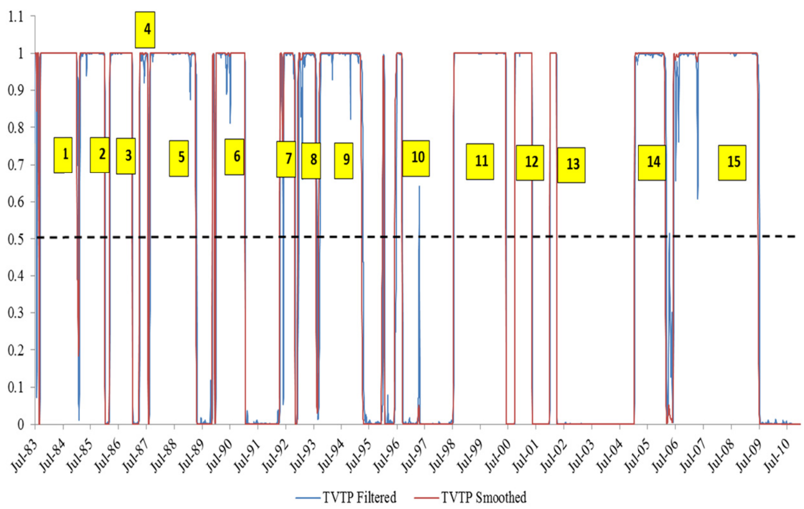
Finally based on the discriminating power of the model in segmenting the states and likelihood test carried out in the line with Diebold et al. (1999), and the result supported the MSRM TVTP model over the CTP model both for illiquidity spiral and loss spiral identification. Thus the illiquid and liquid spiral states and loss and non-loss spiral states are identified in the line of the filtered transition and smoothen transition results obtained from the MSRM under TVTP.

5.3 Regime Identification for Illiquidity and Loss Spiral

The identification of the regimes under TVTP both for illiquidity spiral and loss spiral are based on standard deviations, which is obtained from the variance and covariance matrix. The dating of the two regimes both for Illiquidity spiral are schematically presented in Figure 2 and Figure 3 respectively, which plot simultaneously the filtered transition and smoothing (posterior) probabilities of state = 2 are summarized in Table 3. We combine both the filtered and smoothing transition probabilities to determine the illiquidity and liquidity spiral states and loss and non loss spiral states in the US equity market. In addition to that we have taken 0.5 as the cut off value for State =1 or 2. That is, the periods with the filtered and smoothing probabilities of State = 2 greater (less) than 0.5 are more likely to be in the state of high illiquidity spiral and high loss spiral periods respectively. According to this approach, since 1983 the US equity market has been experiencing 15 number of illiquidity spiral periods and 11 number of loss spiral periods. However in general, we observed a few number of occasions, where illiquidity spiral and loss spirals are observed to be persistent in the US equity market during the sample study period. A detailed analysis is resorted hereunder to relate with the events of the switching of illiquidity and loss spiral regimes in US equity market corresponding to our study period.

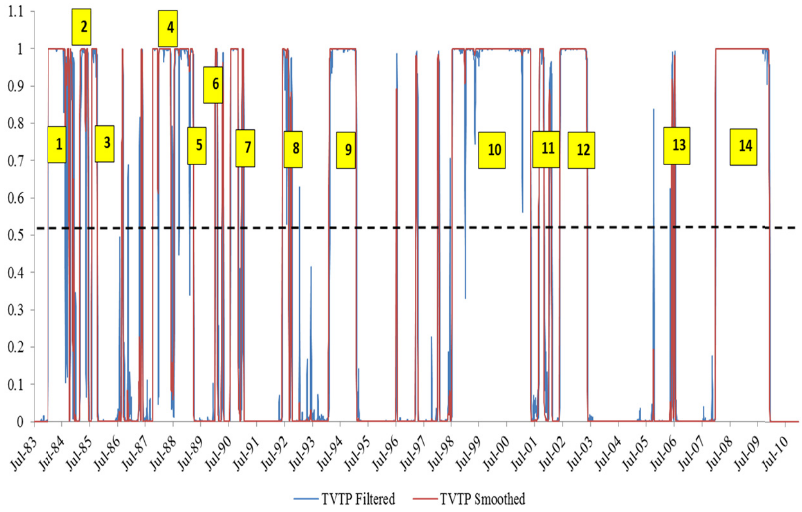
The high illiquidity and the loss spiral spikes during 1987 corresponds to the periods around the Black Monday of October 1987 when stock market around the world crashed, when a few short lived jumps that forced the US equity market to be in high volatile regime. The illiquidity and loss spiral regimes of 1991 can be attributed to the periods in which US engaged in Gulf war especially with the Iraq that culminated in high volatility regimes in the US equity market. Higher jumps in illiquidity spiral and loss spirals during 1997 corresponds to the Asian Financial crisis that led to massive deterioration of wealth in the East Asian economies real estate space, along with the onset of capital controls in Malaysia and blemish advice and numerous conditionality of the IMF to such economies ultimately buckled the confidence of the investors across the world. As a result of such crisis equity market across the world including US went on rampage in the fronts of equity prices and market volatility. The dot com bubble burst could have been responsible for shifting the regimes of illiquidity and loss spiral state around the turn up of the 21st century. Further the 9/11 attack of World Trade Center coupled with the recession in US economy elongated the illiquidity and loss spiral jumps in the US equity market towards the end of the year 2001 and entire 2002. The staggering inflation and high energy prices in the US economy around 2005 further created uncertainty in the economy as a result of which equity market experienced regime shift in illiquidity spiral for a period of 13 months and loss spiral approximately for a very short period of about a month. Specifically the US equity market experienced a prolonged period of illiquidity spiral for almost a period of two years and loss spiral for a period of almost a year due to the onset of the 2008 global financial crisis that originated in US and suddenly contaminated the financial, monetary and asset markets across the world.

However, examining the identified periods more closely it is affirmed that illiquidity spiral and loss spiral grew rapidly across the macroeconomic stress periods. The level of average illiquidity spiral and loss spiral were spiking high during NBER identified recessionary periods of 1987, 2000 and 2008 whereas the average illiquidity spiral before and after the recession for the respective periods the level of illiquidity spiral and loss spiral were observed to be very low. This explains why the Markov switching model classifies all the average level of illiquidity spiral values into two different states when the full sample is considered. Nevertheless, from Figure 2 and 3 of the smoothing probabilities curve we can see that illiquidity spiral and loss spirals are still experiencing some ups and downs across the periods. However the average levels of illiquidity spiral and loss spiral values are relatively experiencing higher levels of ups during major US recessionary periods and down around the periods of tranquility or market up turn. It is very interesting to note that the period around the global financial crisis (2008) the US equity market has experienced the longest period of illiquidity and loss spiral. Thus it is affirmed that there is simultaneity between illiquidity and loss spiral occurrences in the US equity market at least during the market down turn. That means on an average a period of high illiquidity spiral goes in hand in hand with the period of high loss spiral at least during recessionary period.



Period	Start	End
1	9/7/1983	10/18/1984
2	2/28/1985	1/14/1986
3	3/31/1986	1/2/1987
4	4/28/1987	5/26/1987
5	7/2/1987	1/27/1989
6	1/16/1990	12/26/1990
7	5/11/1992	10/1/1992
8	12/30/1992	8/2/1992
9	10/1/1993	3/21/1995
10	7/3/1996	9/11/1996
11	7/28/1998	4/27/1999
12	10/16/2000	4/21/2001
13	1/10/2002	4/5/2002
14	1/20/2005	2/16/2006
15	6/20/2006	6/16/2009

Figure 2. Illiquidity spiral identifications under Markov regime switching time varying transition probability (TVTP) with S&P 500 return with start and end period details



Period	Start	End
1	1/16/1984	8/7/1984
2	3/15/1985	6/5/1985
3	8/14/1985	10/9/1985
4	10/19/1987	6/30/1988
5	8/15/1988	3/29/1989
6	1/17/1990	2/7/1990
7	8/6/1990	11/9/1990
8	6/12/1992	9/3/1992
9	2/14/1994	2/7/1995
10	6/21/1998	5/18/2001
11	9/7/2001	11/6/2001
12	6/5/2002	5/22/2003
13	6/13/2006	6/28/2006
14	1/8/2008	12/10/2009

Figure 3. Illiquidity spiral identifications under Markov regime switching time varying transition probability (TVTP) with S&P 500 return with start and end period details

6. Conclusion

It is concluded that the Markov switching regime model with CTP and TVTP delineates clearly the two states of illiquidity spiral and loss spiral in US equity market under the study period. Further illiquidity spiral state is relatively longer than that of the loss spiral state, which perhaps indicate that illiquidity spiral and loss spiral don't move together always in the US equity market. While examining the transition probability matrix and the expected durations of the both the states it is affirmed that there is considerable state dependence in the transition probabilities with a relatively higher probability of remaining in the origin regime for illiquidity spiral and alternate regime for loss spiral obtained from the CTP switching regressions. The closer examination of the constant transition probabilities and time varying transitional probability affirm that the periods can be easily identified under two states both for illiquidity spiral and loss spiral in the US equity market under the study period. While selecting the suitable model for identification of illiquidity and loss spiral regime switching TVTP model is preferred over the CTP model due to its better predictability that emerged out of the likelihood test. Thus the identification of illiquid and liquid spiral states and loss and non loss spiral states is carried out in the line with the filtered transition and smoothen transition results obtained from the Markov Regime Switching TVTP Model. In nutshell, we have identified 15 stretches of illiquidity spiral and 14 stretches of loss spiral in the US equity market from 1983 to 2010. However, it is also observed that the illiquidity and loss spiral do not always corresponds to each other but they occur simultaneously during the extreme market conditions. Such joint occurrence is termed as liquidity spiral which is observed to be a rare phenomenon in the US equity market. Thus the findings of our study support the study of Jain, Mishra and McInish (2013) and identified the periods of high liquidity particularly during the macroeconomic stress periods.

The study reports several implications on the need to monitor the liquidity spiral occurrences and take up the appropriate policy measures. Under the intense liquidity spiral conditions, the role of financial systems like banks- becomes more crucial as the market dried up due to high illiquidity. The timely channelization of fund to the market could subsidies the intensity and prolong period of liquidity spirals phenomena. Our proposed measure provides an instrumental tool which can be used to gauge and identify the trigger of the severe illiquidity. The paper contributes to the literature by modeling and identifying the periods of illiquidity spiral and loss spiral in the equity market with focus on US. The study also supports the existing literature that small size firms are more vulnerable to spiral intensities than the large size firms. Further it is concluded that the occurrence of spiral phenomenon are rare in nature and it appears during the extreme market down turn periods. Future research in this direction could focus impact of political uncertainty, drastic change in regulatory norms (relating to forex policies, monetary policy, fiscal policy, trade policy and public debt policy), government austerity measures, inflation persistence, major world events, natural calamity, terrorist attack and waging wars might have a linkage with the liquidity spiral phenomenon. Further the study on liquidity spiral contagion across the economies would no doubt a fortified field for future research.

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Note

Note 1. For details, see Bouson, Stahel and Stulz (2010).