

**FINANCIAL SPILLOVERS FROM THE US FINANCIAL  
MARKETS TO THE EMERGING MARKETS  
DURING THE SUBPRIME CRISIS:  
THE EXAMPLE OF INDIAN EQUITY MARKETS**

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# **Financial spillovers from the US financial markets to the emerging markets during the subprime crisis: the example of Indian equity markets**

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## **Abstract**

This paper provides evidence of spillover effects from the Indian to the US financial markets. We use VAR and Kalman filter analysis to assess the influence of financial stress indicators like the LIBOR-OIS, CDS, the S&P 500 volatility and the exchange rate of the rupee against the Dollar on two indicators of financial stress in India, namely the illiquidity of stock indices and their volatility. We conduct an analysis based on both daily and monthly frequency and use a database that consists of both aggregate and disaggregated indexes. Our results point to a significant contagion effect after the period following the Lehman Brothers collapse.

**Key words** : Subprime crisis, Emerging Markets, VAR analysis, financial stress

**JEL Classification** : F37, G15, O53.

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# **Financial spillovers of the subprime crisis on the Indian equity markets: some empirical evidence**

## **1.- Introduction**

The aim of this paper is to provide evidence of spillover effects of the recent financial crisis (subprime crisis) on the Indian equity markets. Financial spillovers during a crisis are sometimes analyzed, in the finance literature, as the existence of co-movements between asset returns driven by structural shocks. This definition stresses the increased correlation between returns after a shock originating from one market as compared with observed correlations in normal times. Typical empirical models used are multivariate GARCH models (see for instance, Frank and Hesse (2009)). In the current paper, we consider change over time in the dynamic process of transmission of shocks from the US financial markets to the Indian equity markets. The empirical models are based on the interpretation of the impulse response functions of VAR models in which we examine how different stress indicators in the Indian stock markets react to changes in the US financial variables. We further consider the time-varying influence of the latter by estimating simple linear regressions based on Kalman-filter models. We do not search to explain the main transmission mechanisms, but simply to show some stylized facts about possible spillover effects of the subprime crisis in India.

Some papers investigate changes over time in the conditional correlations between markets during times of financial crises (for instance, King, Sentana and Wadhvani (1994), Corsetti, Pericoli, and Sbracia (2005)). Other papers identify the transmission mechanisms of shocks (Dungey, Fry, Gonzalez-Hermosillo and Martin (2005), Kaminsky, Reinhart and Végh (2003)). However, these papers focus on studying correlations among similar countries (developed countries on one side and emergent markets on the other side). However, papers examining the transmission of shocks from mature to emerging markets are few (Psalida and Sun (2009), Frank and Hesse (2009), Beirne, Caporale, Schulze-Ghattas and Spagnolo (2008)). Our paper is a further contribution to this recent literature but focuses on India, one of the biggest emerging countries in the world.

This investigation is important insofar it provides some evidence against the idea of a financial decoupling between the Indian and US stock markets during the subprime crisis. This paper contributes to the existing literature by considering, at a daily frequency, several kinds of spillover effects such as market volatility spillover, liquidity spillovers from the US to Indian markets. We analyze these effects by considering both aggregate and individual stock indices. More specifically, we consider the effects of stress in the interbanking market, of solvency concerns of US financial

institutions as measured by the CDS spreads and of US stock market risk measured by the volatility of the S&P 500.

The remainder of the paper is organized as follows. Section 2 presents the data. In Section 3, we give some qualitative features of financial stress in the Indian equity markets during the subprime crisis. Section 4 contains the results of our empirical investigation of transmission effects from both VAR models and Kalman filter equations. Finally, Section 5 concludes.

## **2.- Data**

We first consider a global equity index, the BSE SENSEX quoted in the Bombay stock market. It is made of the 30 most actively traded stocks and tracks more than the two-thirds of total capitalization. We further consider 12 individual stocks: ACC Ltd., Grasim Industries Ltd., HDFC Ltd., Hindustan Unilever Ltd., ICICI Bank Ltd., Larsen & Toubro Limited, Mahindra & Mahindra Ltd., ONGC Ltd., Reliance Infrastructure Ltd., Sun Pharmaceutical Industries Ltd., Tata Motors Ltd., State Bank of India.

The data sample ranges from January 2000 until March 2009 and consists of daily observations. To account for financial stress in the Indian stock markets, we define several variables. First, the variance of returns serves as a proxy of market volatility. It is measured by either the squared returns or the in-sample forecasts obtained from a GARCH(1,1) model. Secondly, we consider indicators of liquidity risk in the stock markets to reflect a situation in which investors may not be able to sell or buy an asset at a price close to the preceding traded prices. The two proxies we consider for capturing this are the spread between the bid and ask prices, and, a illiquidity ratio proposed by Amihud (2002).

As measures of financial stress in the US stock markets, we consider the following variables. Firstly, as a measure of funding liquidity in the US interbank market, we consider the daily 3-month US dollar Libor overnight index swap (LIBOR-OIS). A second variable captures the default risk of large US financial institutions (we compute the average of their credit default swap spread (CDS spreads). Thirdly, to account for the high uncertainty that has characterized the stock market during the 2008 financial turmoil, we consider the volatility of the S&P 500 index. Finally, we consider the exchange rate of the Indian Rupee against the dollar. Indeed, because India has an open capital account, portfolio movements during the crisis may have been a cause of financial-to-financial spillovers. All these variables are measured at a daily frequency.

The sources of the data are the following:

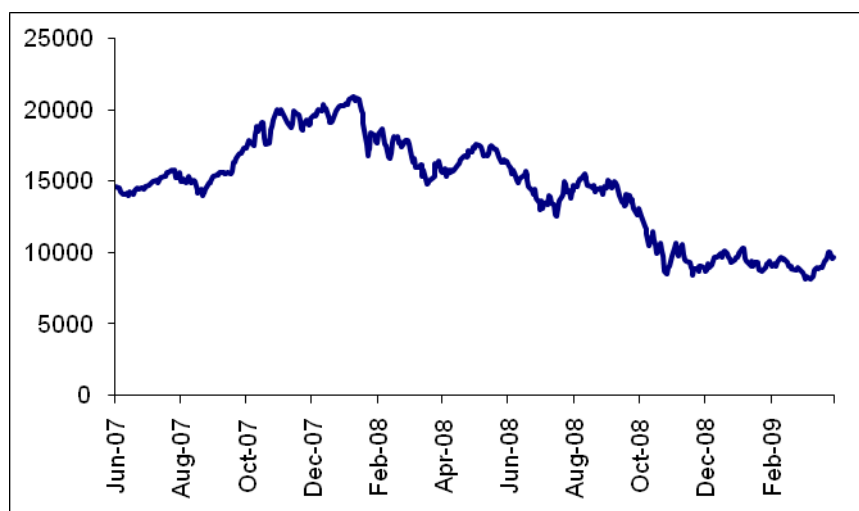
Equity stock prices and turnover data are taken from the database of the Bombay Stock Exchange), the bid, ask and midpoint series used to compute the illiquidity ratio comes from FININFO, the data from US are taken from Boomborg.

### 3.- Some stylized facts about Indian financial stress indicators during the crisis

#### 3.1. Stock market volatility

Figure 1 shows that the Indian stock market exhibits the first signs of fragility since the beginning of the year 2008<sup>1</sup>, when the crisis deepens. The BSE SENSEX index drops of 19% between January and March 2008. This drop coincides with an announcement by Merrill Lynch, on the 17<sup>th</sup> of January 2007, of a US\$ 9,8 billions loss in its balance sheet for the fourth quarter of 2007; it coincides also with announcement - by H. Paulson, the U.S. Secretary of the Treasury - of the first Emergency Economic Stabilization (commonly referred to as a bailout of the U.S. financial system). A new 33% drop follows this fall between September and November 2008. On the whole, the index displayed a 50% decrease for 2008 onwards. Such a path provides evidence of the uncertainty hanging over an Indian market more and more volatile during the period.

Figure 1.- BSE SENSEX index from June 2007 to March 2009



<sup>1</sup> Just after the U.S. financial collapse of summer 2007, the emerging markets – considered as a “safer heaven” - benefited from international capital inflows coming from the matured markets. This explains the steady growth of the BSE SENSEX during the second semester 2007.

Figures 2 and 3 reproduce the respective time paths of the level and squared returns for the BSE SENSEX index. Both figures exhibit a significant increase in the volatility between the second quarter of 2007 and the end of 2008. Figures 4 and 5 show the squared returns of the individual stocks. The volatility dynamics displays several episodes. From August 2007 to the mid-2008, it swings around 5%; then, it increases sharply at the beginning of September 2008, displaying fluctuations above 10%. During the 24<sup>th</sup> of October, a day pointed out as an historical one, the worldwide indexes experience exceptional drops and the BSE SENSEX goes down by 10,9%, the higher decrease being noticed for the values of ICICI Bank, ONGC and the State Bank of India (respectively 15,1%, 15%, and 12.6%).

Figure 2.- BSE SENSEX return from June 2000 to March 2009

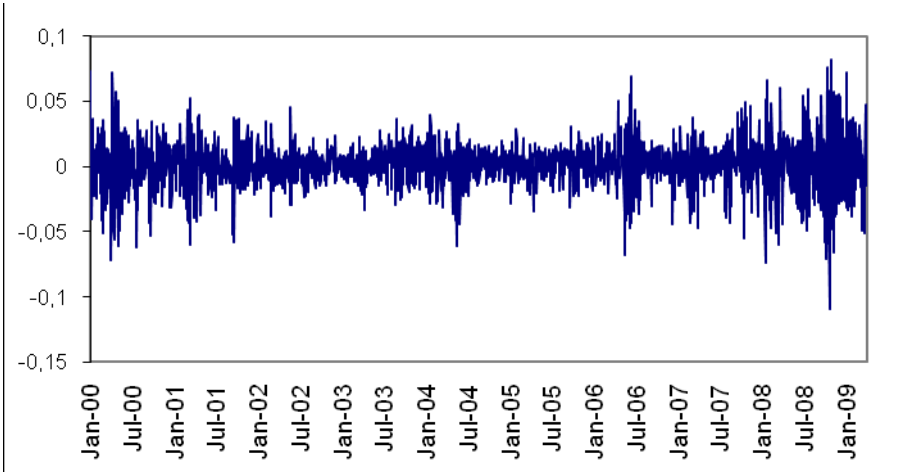
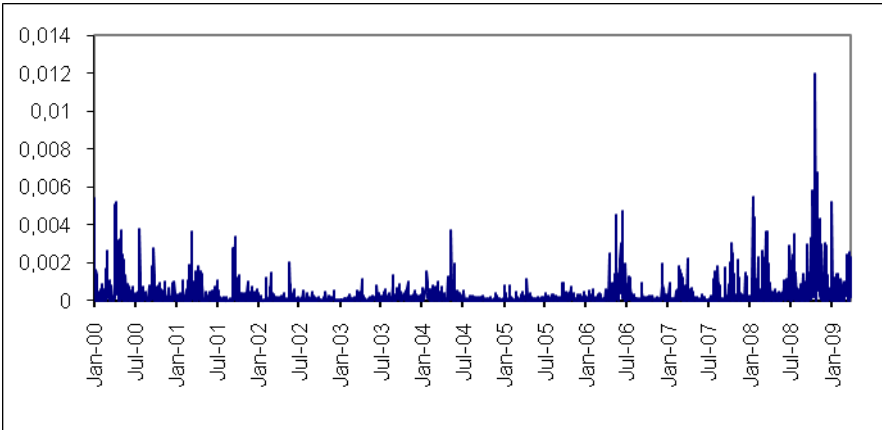


Figure 3.- BSE SENSEX (squared returns) from June 2000 to March 2009



The descriptive statistics displayed in Table 1 exhibit high values for the kurtosis (over 3 in all cases), suggesting the leptokurtic feature of indexes distributions (with a high peak around the

mean). Furthermore, these indexes show fat tails at their low extremities as well as left or right asymmetries. These observations, in addition to the conclusions drawn from the Jarque Bera test lead us to reject the normality hypothesis for all the distributions.

Figure 4.- Squared returns of individual indexes from June 2000 to March 2009

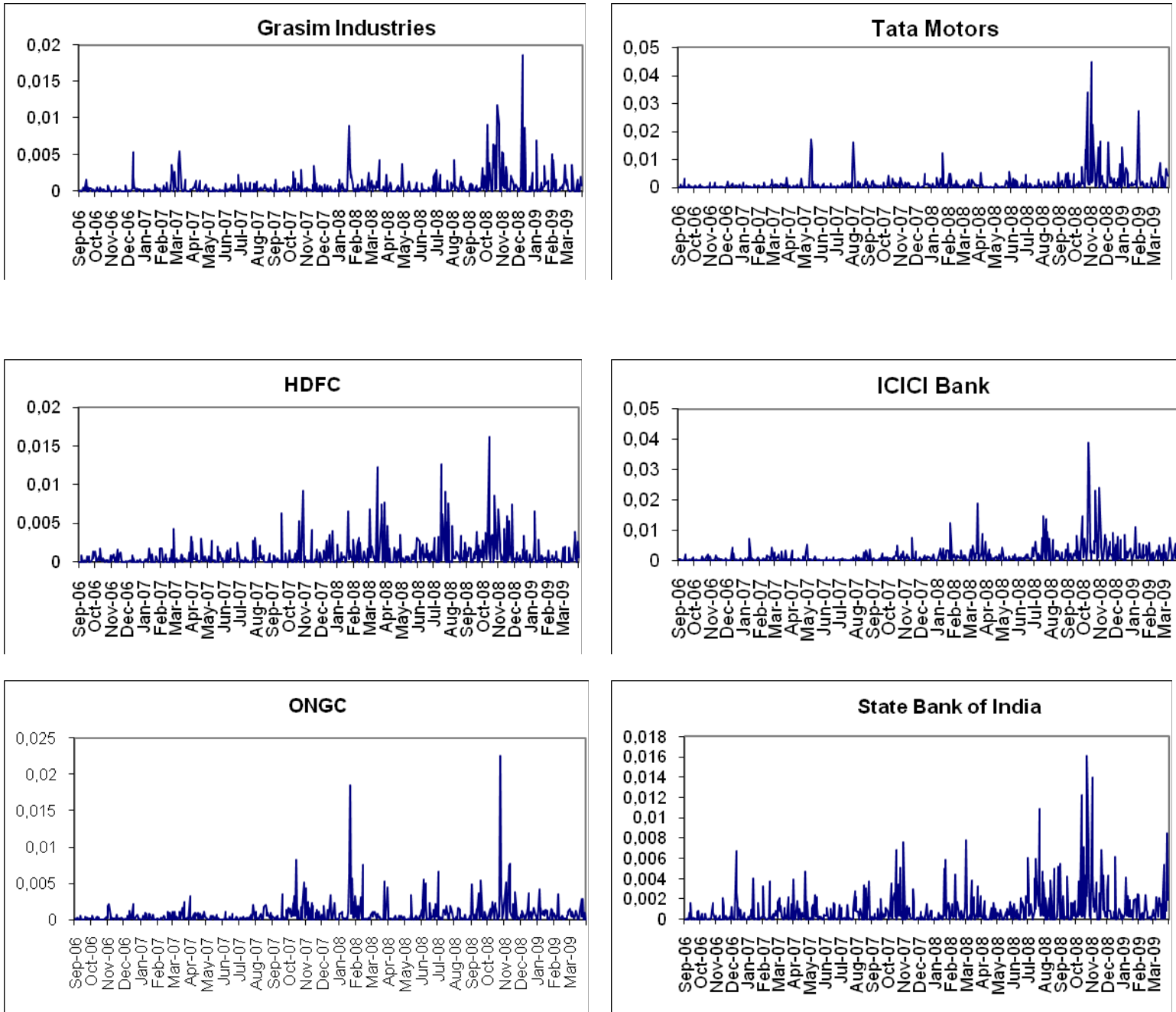
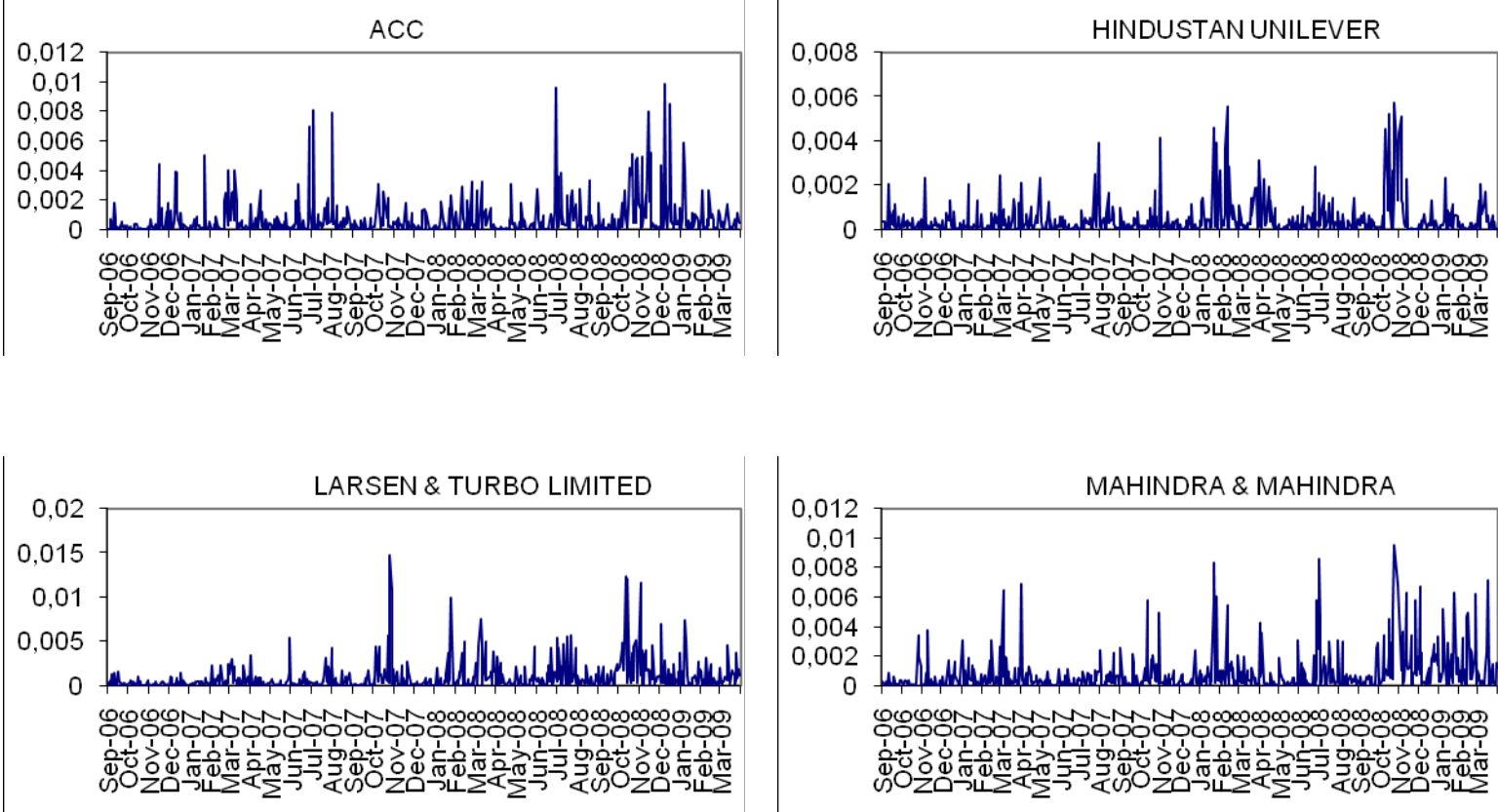


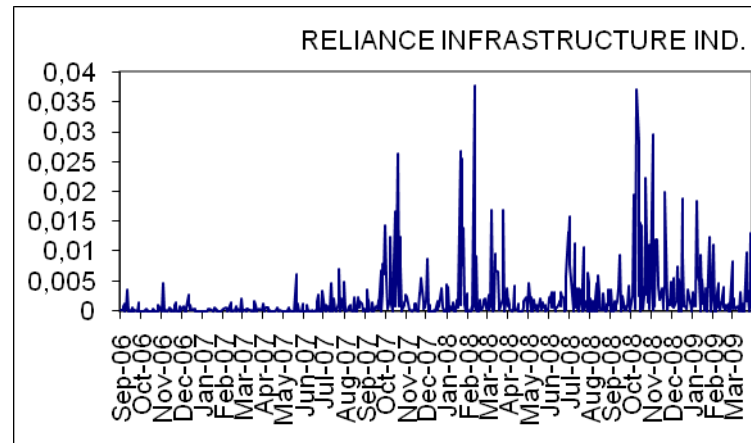
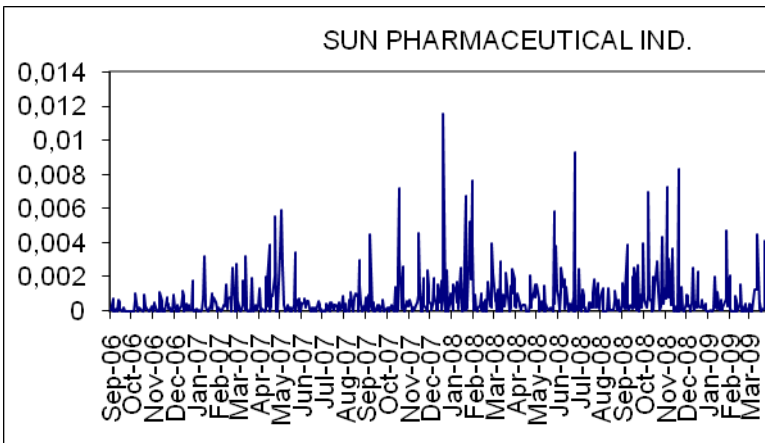
Table 2 exhibits the results of GARCH(1,1) models applied to our data. It can be observed that the volatility is highly persistent (the sum of the estimated coefficients is close to 1). As an illustration, Figures 6 and 7 reproduce the path of conditional variance using the GARCH models estimates<sup>2</sup>. While the volatility is increasing from the second semester of 2007, it speeds up suddenly at the start of 2008. Yet, among all the securities, some are less hit: GRASIM INDUSTRIES, ICICI Bank, and Tata Motors.

Figure 5.- Squared returns of individual indexes from June 2000 to March 2009



<sup>2</sup> The peak of July 2006 is due to Bombay train bombing.





The evolution of the index BSE SENSEX conditional variance leads us to conclude that in the beginning of 2008 the Indian stock market has been hit and after a fairly turbulent time, a peak in the volatility was reached at the end of the year. The volatility became extreme in September 2008, after the announcement of the default of several U.S. financial institutions (on September 15, 2008, Lehman Brothers Holdings Inc. announced that it failed getting assistance from the FED and finding a buyer for a majority stake of its capital).

After December 2008, the volatility decreases; but this movement can hardly be interpreted as a sign of a markets lull. Above all, this reflects a “flight to quality” phenomenon, at a time when the investors were giving up the emerging markets in the early times of the world recession to take shelter temporarily on the safer bonds market of the industrialized countries.

Table 1. – Descriptive statistics and ADF tests

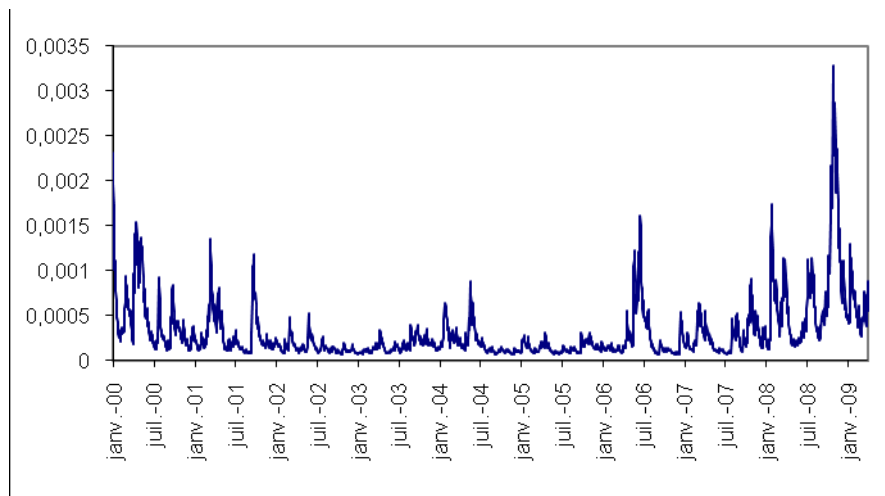
Stock index	Skewness	Kurtosis	Jarque Bera	ADF level ADF (difference)
BSE SENSEX	-0.294687	6.095488	924.6760 (0.0000)**	-40.55695 (-3.433081)***
ACC	-0.134238	6.393456	1087.788 (0.0000)	-46.82763 (-3.433058)
State Bank Of India	0.046603	5.133989	427.9337 (0.0000)	-40.55695 (-3.433060)
Grasim Industries	0.081512	6.500975	1153.105 (0.0000)	-44.84349 (-3.433058)
HDFC	0.221437	5.947095	829.6804 (0.0000)	-35.52161 (-3.433073)
ICICI Bank	0.240645	6.372685	1094.893 (0.0000)	-33.48007 (-3.433045)
Larsen & Toubro Limited	0.067692	5.085408	404.8809 (0.0000)	-34.74426 (-3.433095)
Mahindra & Mahindra	-0.112237	5.333038	514.0958 (0.0000)	-33.70321 (-3.433068)
ONGC	0.015100	5.858878	765.2997 (0.0000)	-34.84168 (-3.433067)
Sun Pharmaceutical Ind.	0.015100	5.858878	765.2997 (0.0000)	-34.84168 (-3.433067)
Tata Motors	-0.095788	6.489415	1143.415 (0.0000)	-43.85091 (-3.433065)

Notes: \*The ADF regressions include an intercept \*\*probability of not rejecting the null hypothesis of a Normal distribution \*\*\*Critical value at 1% level of significance

Table 2. GARCH models :  $\sigma_t^2 = \omega + \alpha\sigma_{t-1}^2 + \beta\sigma_{t-1}^2$

	$\omega$	$\alpha$	$\beta$	$\alpha + \beta$
BSE SENSEX	8.91E-06	0.152787	0.817501	0,970288
ACC	2.00E-05	0.130046	0.849272	0,979318
State Bank Of India	1.37E-05	0.081741	0.896216	0,977957
Grasim Industries	1.16E-05	0.098751	0.885481	0,984232
HDFC	2.28E-05	0.160830	0.806165	0,966995
Hindustan Unilever	2.47E-05	0.109372	0.838772	0,948144
ICICI Bank	2.09E-05	0.093760	0.886351	0,980111
Larsen & Toubro Limited	1.85E-05	0.113825	0.862041	0,975216
Mahindra & Mahindra	2.74E-05	0.113175	0.853186	0,966361
ONGC	1.07E-05	0.088487	0.897973	0,98646
Reliance Infrastructure	1.99E-05	0.110135	0.869333	0,979468
Sun Pharmaceutical Ind.	9.95E-06	0.087022	0.898369	0,980712
Tata Motors	2.15E-05	0.092585	0.881825	0,97441

Figure 6.- Estimated conditional variance from GARCH(1,1) models – Index BCE SENSEX



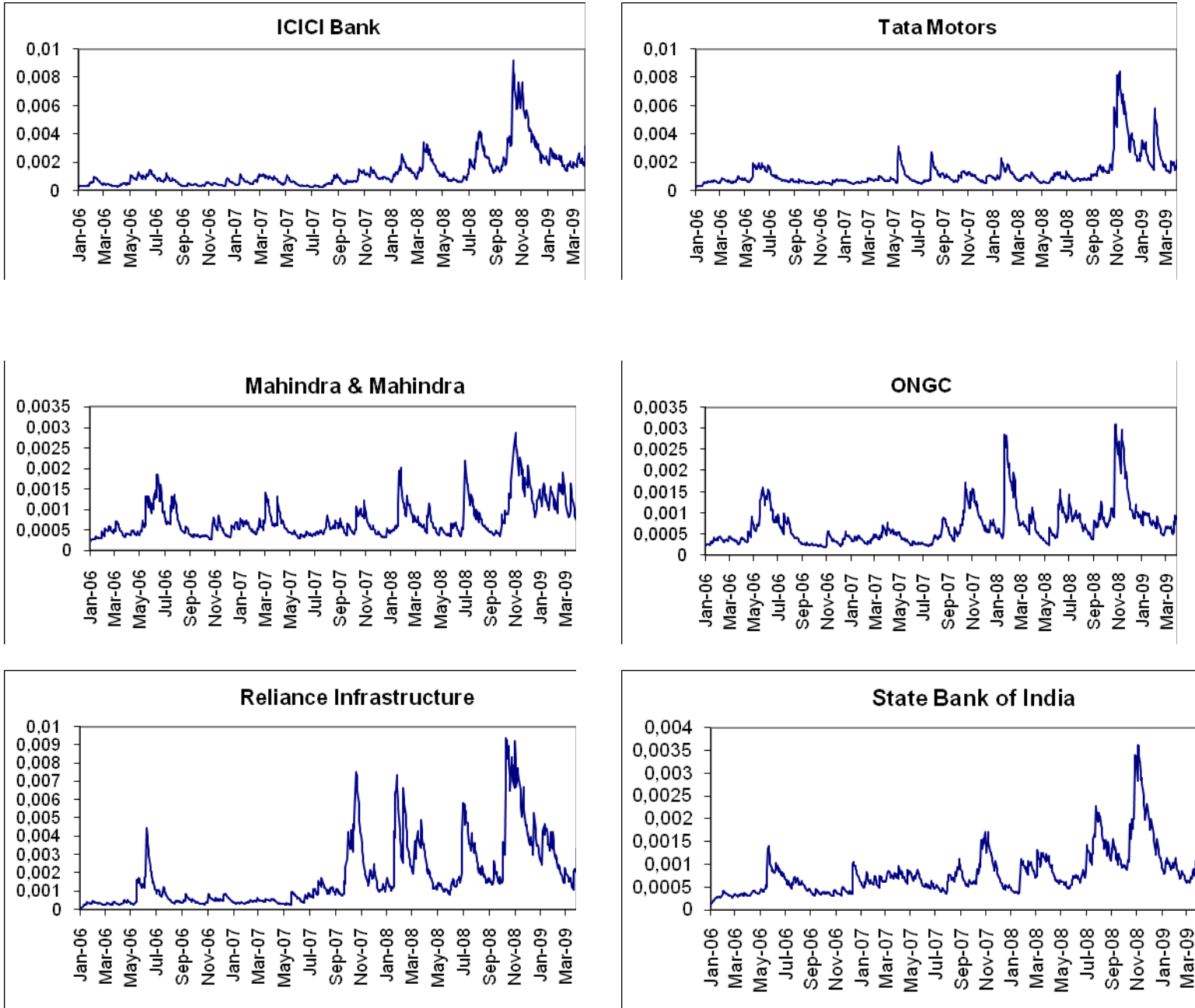
### 3.2. Liquidity risk

We compute the following index for all the assets:

$$SPREAD_t = \frac{|Bid\ price_t - Ask\ price_t|}{Midpoint_t} \quad (1)$$

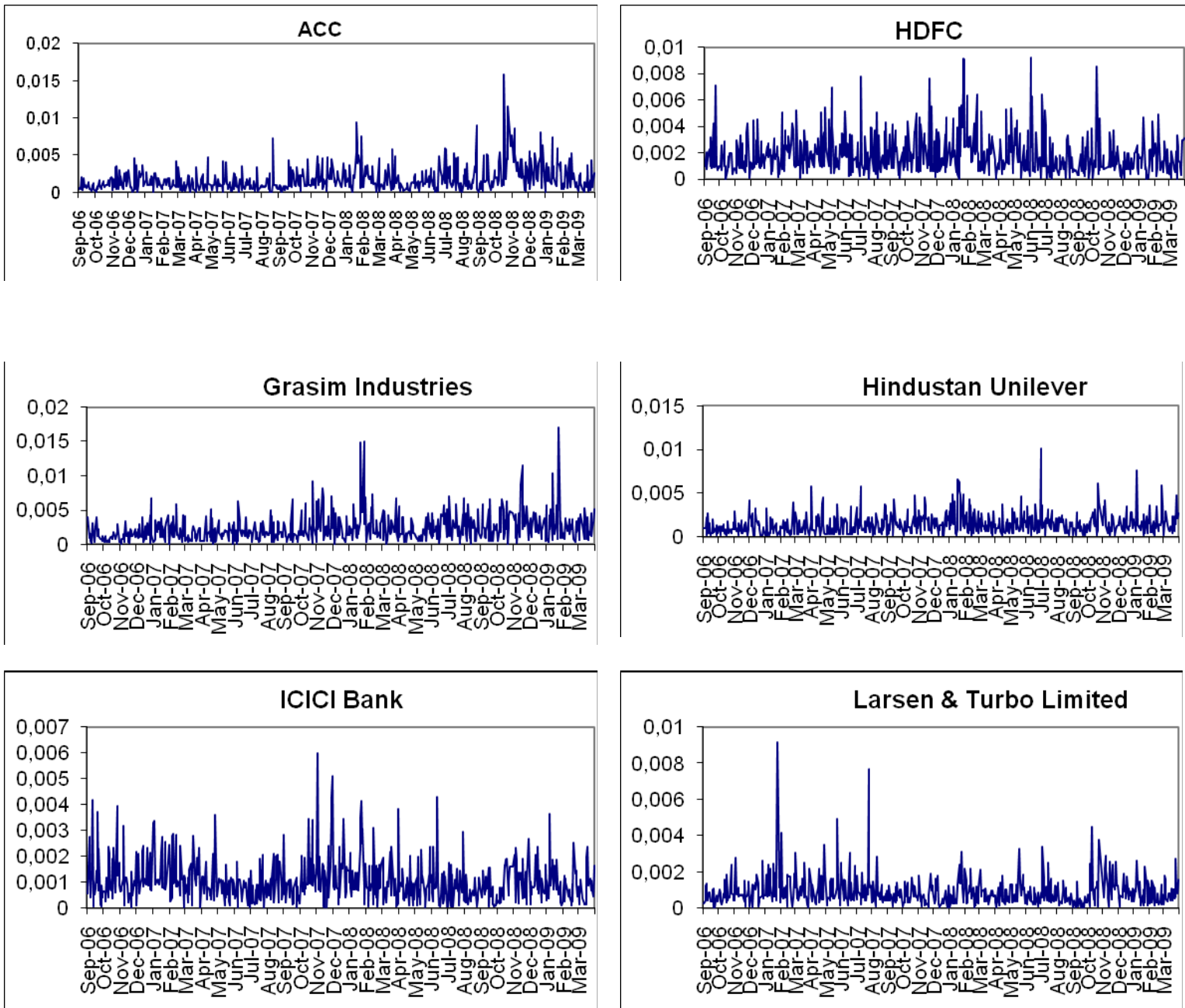
Figures 8 and 9 present the spreads for the different equities. For at least seven indices, the spread increases significantly during 2008, particularly during the second semester (Grasim Industries, ACC, Mahindra & Mahindra, ONGC, Tata Motors, Sun Pharmaceutical Ind., ICICI Bank).

Figure 7.- Estimated conditional variance from GARCH(1,1) models – Selection of individual indexes



It is weaker before and after this period, indicating a more prominent shock on the liquidity level during the second stage of the financial crisis (when the US financial system were collapsing).

Figure 8. Spread for individual indexes

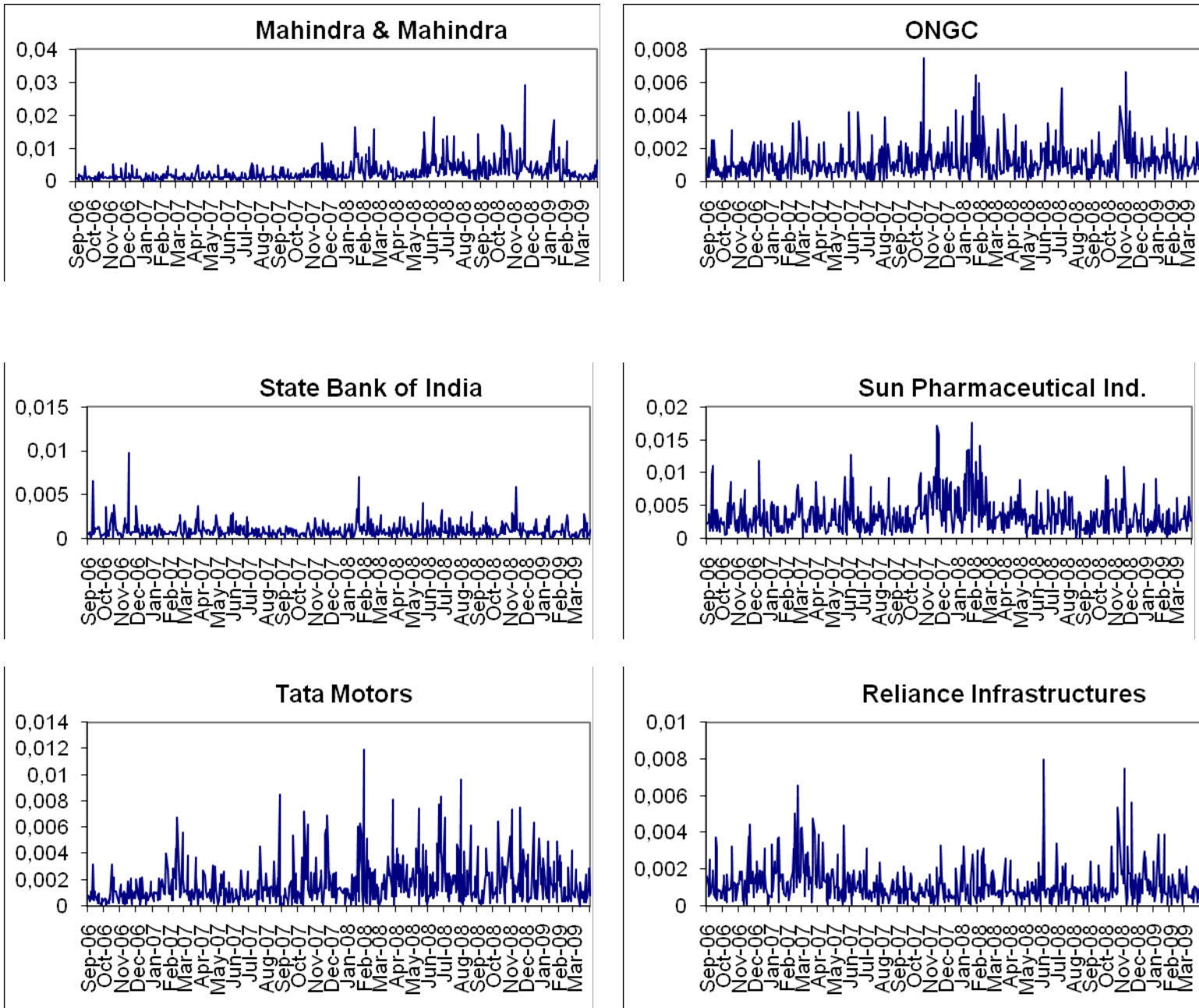


Furthermore, we computed an illiquidity index by adopting the definition proposed by Amihud (2002). It is defined as the ratio of absolute value of return and of the trade volume:

$$ILLIQ_{i,d} = \frac{|R_{i,d}|}{T_{i,d}} \quad (2)$$

where  $ILLIQ_{i,d}$  measures illiquidity for an index "i", on the "d" day.  $R_{i,d}$  is the return of this security for the same day and  $T_{i,d}$  indicates its daily trade volume.

Figure 9. Spread for individual indexes

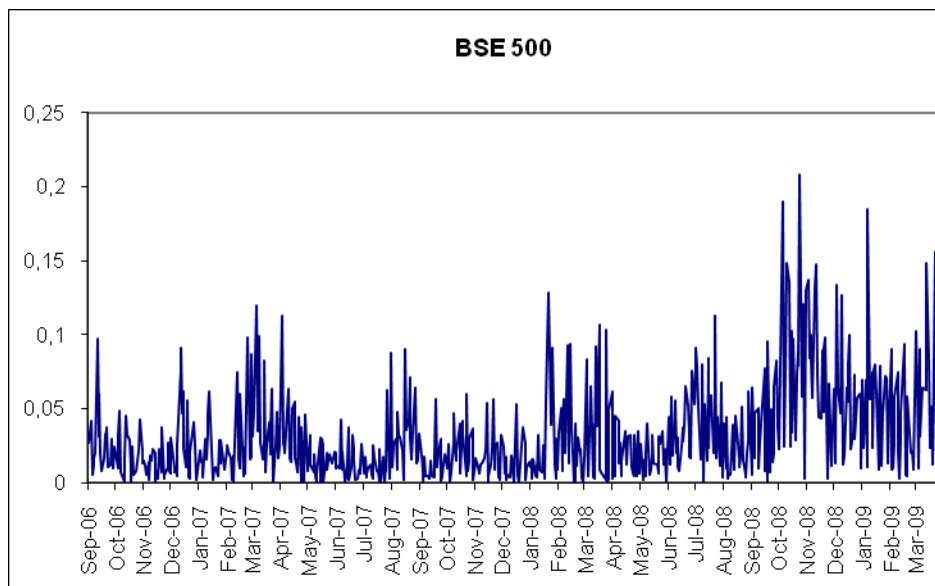


The meaning of the ratio  $ILLIQ_{t,d}$  is fairly intuitive. It represents the impact of the trade volume, in domestic currency on the price change (more currently called price impact). The higher the ratio  $ILLIQ$ , the more illiquid the market (and vice versa). Besides, a significant change in the price associated to a weak trade volume leads to a ratio increase (the price impact is high), whereas a weak price change associated to a stronger trade volume entails a ratio decrease (the price impact is weak). We first compute this ratio for the aggregate index BSE 500. This index is chosen because of

data unavailability of the trade volume for the BSE SENSEX. The BSE 500 represents around 93% of the total Bombay stock market capitalization, regrouping together 500 values of the main Indian industries. The same ratio is computed for the individual indexes. In order to be able to interpret the results, ILLIQ is multiplied by  $10^n$  according to the respective weight of trade volume for each asset.

Figures 10 and 11 show the evolution of the ILLIQ ratio for the BSE 500 index and six values of our sample (chosen as illustration). As it can be checked from the set of graphs, the ratio ILLIQ is relatively weak during the second semester 2007, in spite of a peak in August. The good performance for this period can be explained by the growth of trading activity, more particularly the hedge funds, worried about being able to respond to margin call after the U.S. crisis started in the U.S. (Figure 12). In contrast, the ratio ILLIQ increases significantly in 2008.

Figure 10.- Illiquidity ratio – BSE 500 Index



As noted previously, the volatility rose suddenly during this period. Moreover, Figure 12 shows a drop in trade volume since the beginning of 2008. So, the high level of ILLIQ ratio is not surprising.

Watching at the global index change, we point out that the market liquidity risk (the risk of a generalized disruption in asset markets) rises from January to April 2008, reaching a peak from September to October, following the Lehman Brothers bankruptcy. Thus, we can assume that the sub-primes crisis results in a rise of the liquidity risk on the Indian stock market.



Figure 11.- Illiquidity ratio for a selection of individual indexes

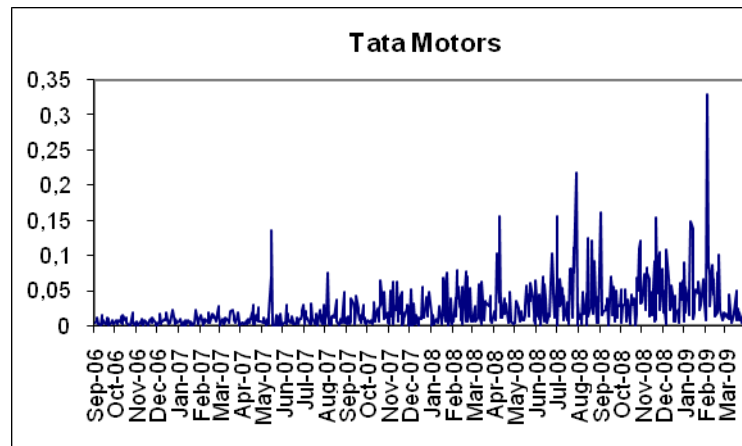
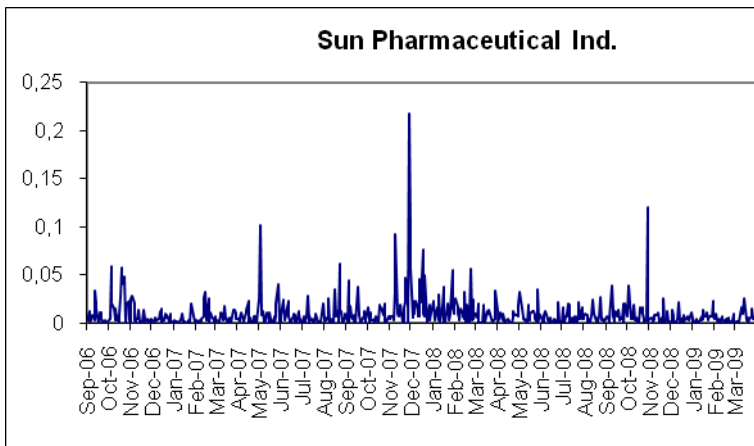
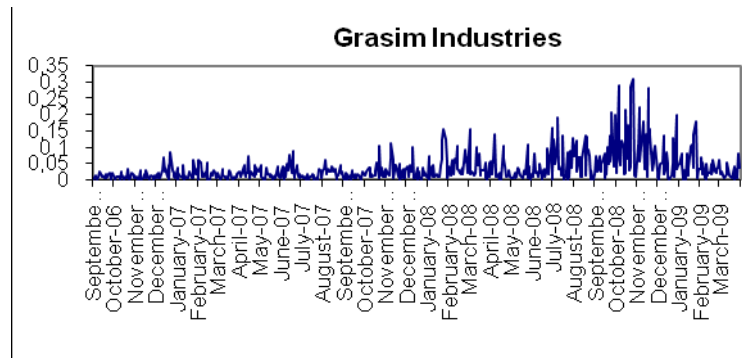
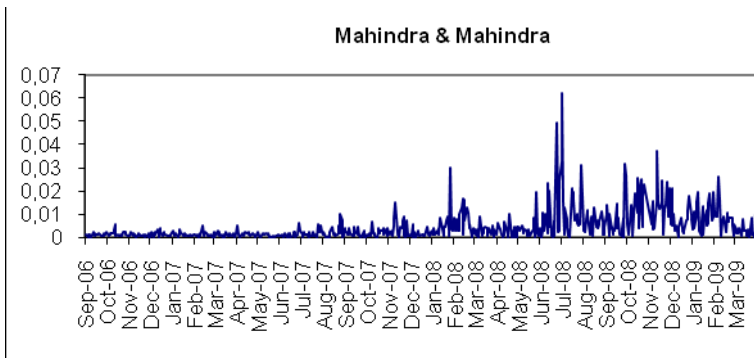
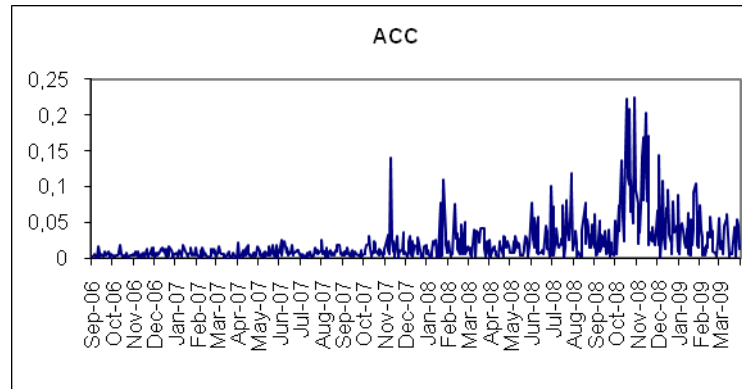
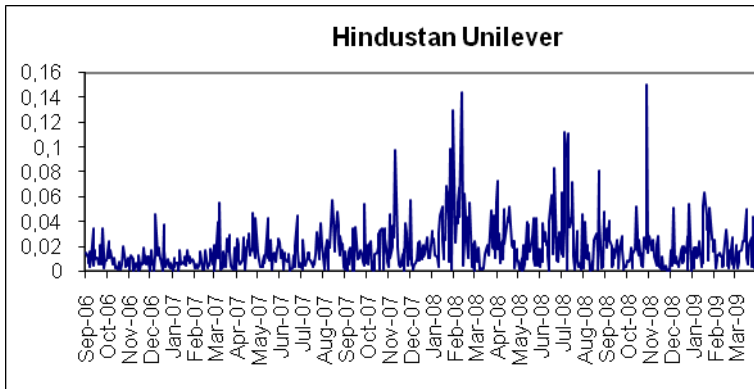
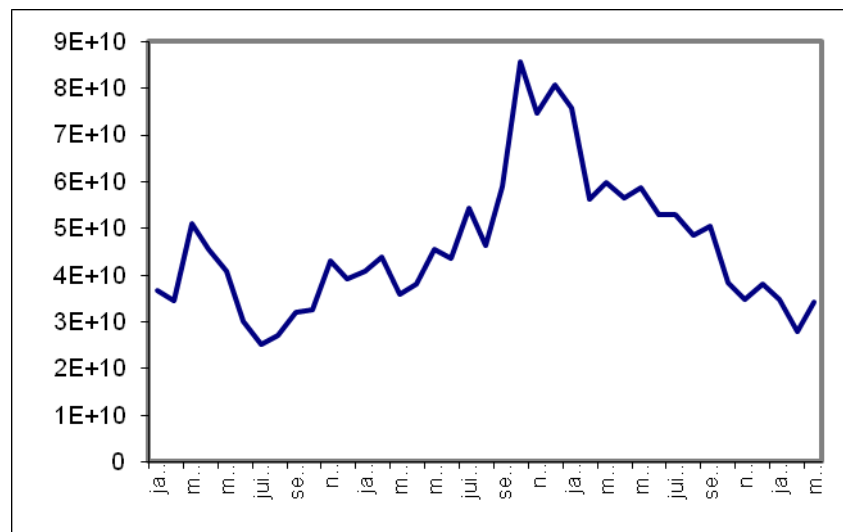




Figure 12.- BSE 500 turnover from January 2006 to march 2009



#### 4.- Evidence of spillover effects from the US markets to the Indian markets: VAR analysis and Kalman filter

We now examine whether the surge observed in the Indian volatility and illiquidity indicators mirrors the financial stress in the US financial market (measured the widening of the LIBOR-OIS spread, the greater volatility in the US stock exchange, the increased risk default and speculative attacks of the Rupee in the exchange rate market...).

In the view, we compute impulse response functions (IRF) from VAR models. We consider bivariate systems composed of a stress indicator in the Indian markets (volatility, illiquidity ratio) and the stress indicators in the US markets. The optimal lags in the VAR are computed according to usual criteria (information criteria, specification tests on the residuals). IRFs are computed using the Choleski decomposition approach.

The impact of shocks is run over a monthly horizon, in order to differentiate the effects due to global financial variables from the perturbations introduced by the market microstructures. Figures 13 to 16 show the dynamics of volatility indexes over the 24 months following financial shocks in the U.S. market.

These evolutions suggest several conclusions. The volatility increases after an impulse on any U.S. financial variable. Figure 13 shows a rise of  $R^2$  and  $\sigma^2$  (the volatility measured respectively by the squared return and a GARCH(1,1) model) of about 0.00015 (i.e. a 1.2% change in returns) and 0.00008 after a 30 days delay (0.9% change in returns), following the impact of a LIBOR-OIS change). As for the credit risk impulse (i.e. spread on U.S. market shown in Figure 14), it causes immediately a

rise of 0.00009 and 0.000004 (0.9% and 0.2% change in returns). At last, a shock on S&P 500 volatility causes immediately a rise of about 0.00015 and 0.00016 (1.22% and 1.26% change in returns) of the respective indexes (Figure 15). The exchange rate impulse also shows an impact on the Indian stock market (Figure 16). The effects are very close to those caused by a LIBOR OIS spread impulse. For the BSE SENSEX index, the persistence of shocks on volatility varies from four to six months. However, the impact disappears after the second quarter. The persistence and the intensity of a specific shock can fluctuate according to the index taken into consideration. Nevertheless, on the whole, the shapes of the responses are the same. In most cases, the impact of a LIBOR-OIS change remains significant after one month and stabilizes definitely during the fifth month in the BSE SENSEX index case.

Figure 13.- Impulse response function of squared return and conditional volatility to a shock on LIBOR

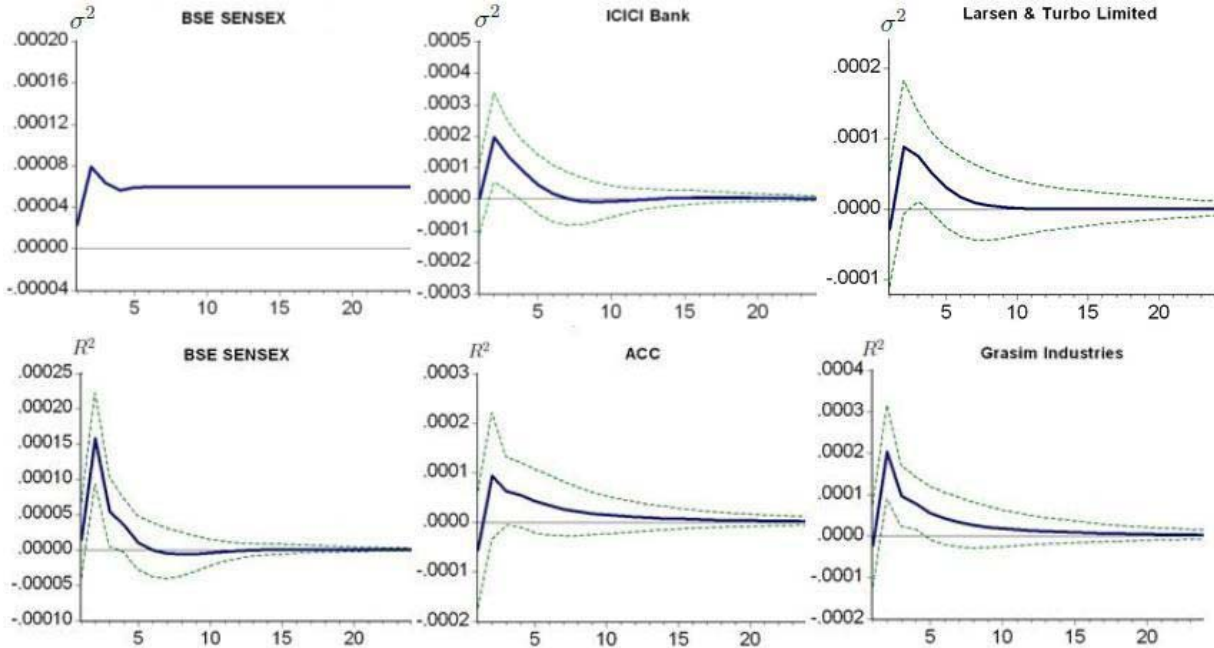


Figure 14.- Impulse response function of squared return and conditional volatility to a shock on the CDS spread

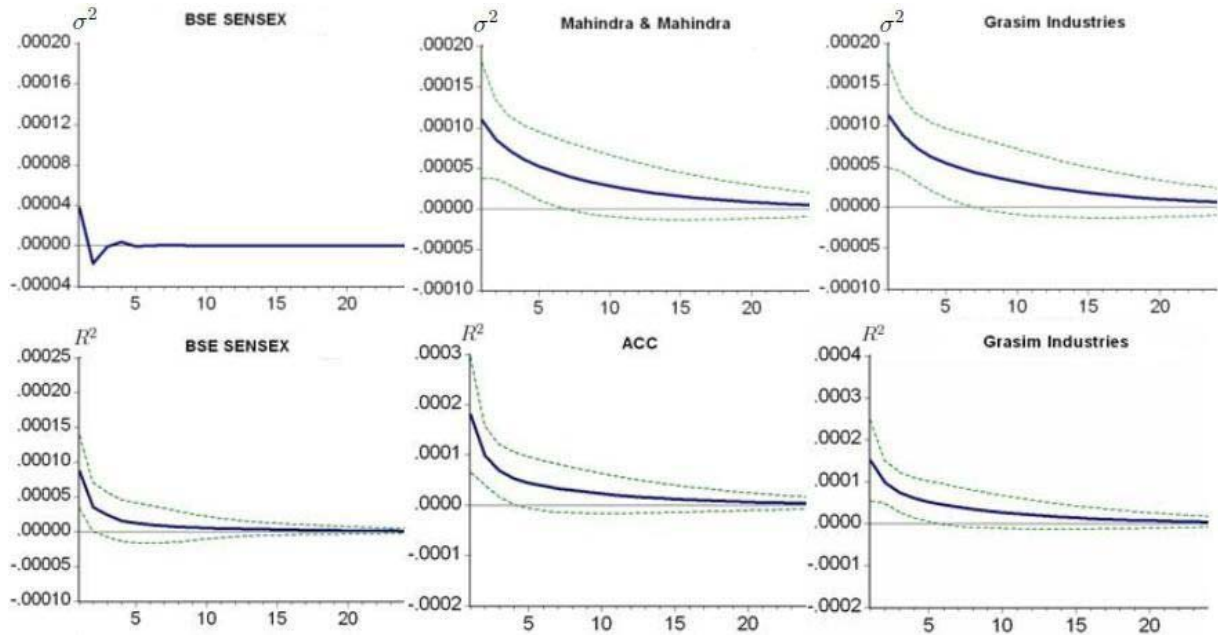


Figure 15.- Impulse response function of a squared return and conditional volatility to a shock on the volatility of the S&P

500

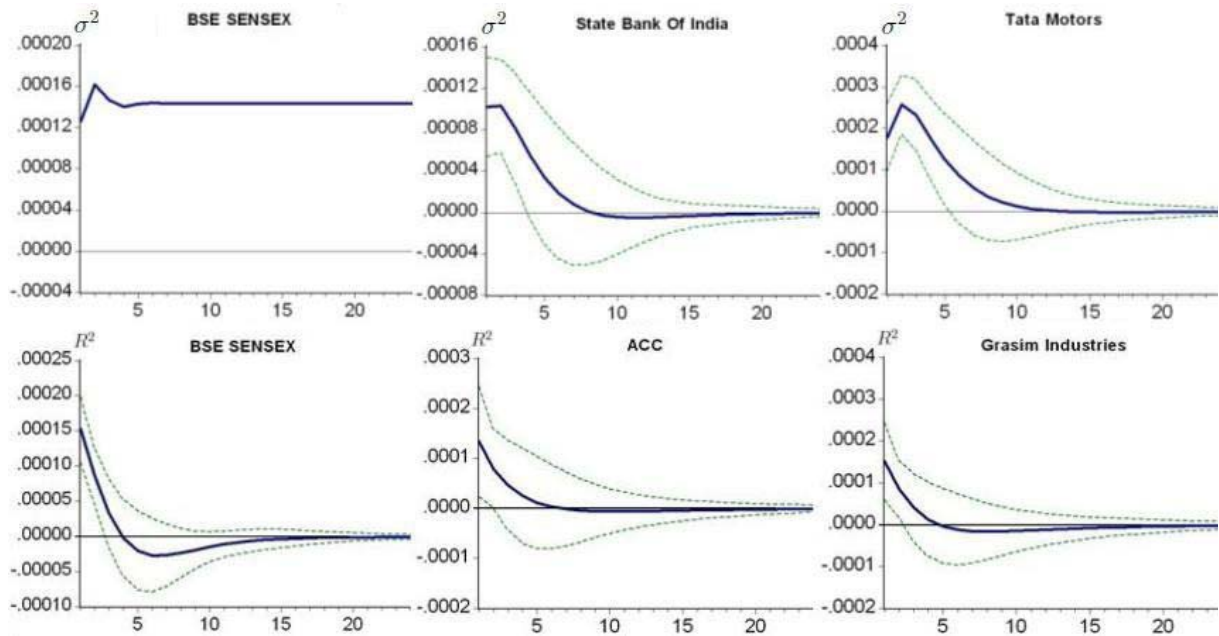
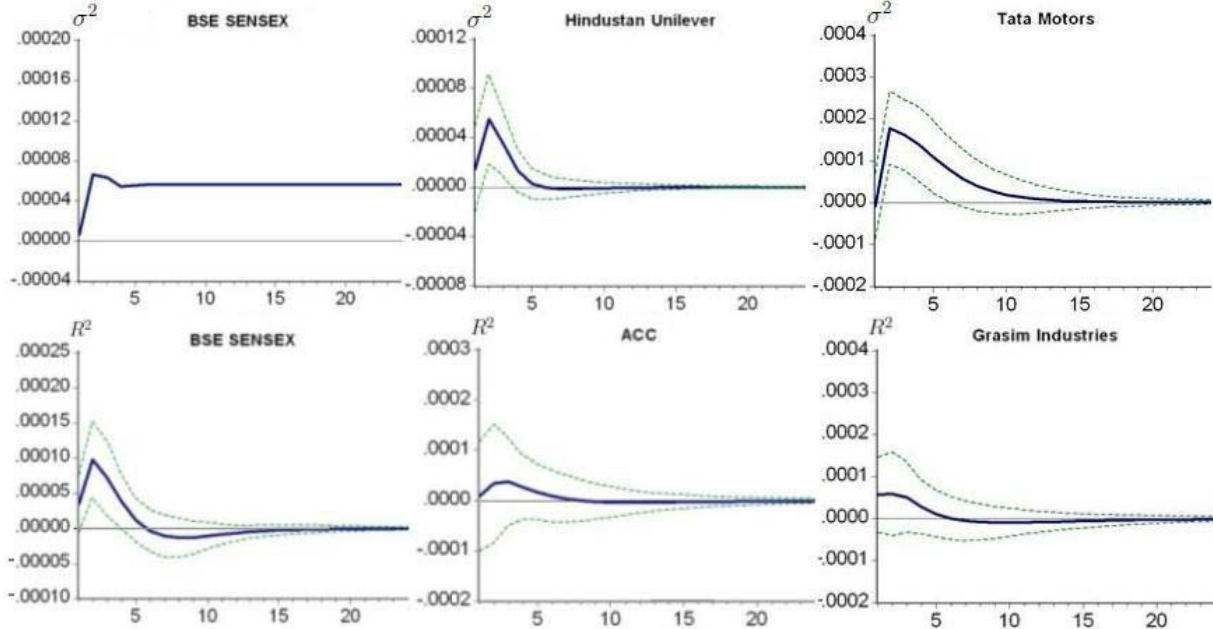


Figure 16.- Impulse response function of squared return and conditional variance to an increase in the exchange rate volatility



Figures 17 to 20 present the responses of liquidity indexes to shocks on U.S. financial variables over 24 months. The graphs on the BSE index 500 point out a rise of liquidity risk in the Indian Stock market following a financial variables impulse. More precisely, the impact of a spread LIBOR-OIS change causes a rise of the ILLIQ ratio of about 0.004 (i.e. a price impact of 0,4%) after 30 days (Figure 17). Regarding the impact of a rise in market risk, it causes an immediate 0.009 increase of the ILLIQ ratio (a 0,9% price impact).

An analysis of the bid-ask spread graphs leads to the same conclusions. However the impact of a SPREAD LIBOR-OIS change causes instantaneously a drop of all the indexes, suggesting in a first step an improvement of liquidity in the Indian stock market. This effect reminds the events of the second semester 2007, when the trading businesses were important in the emerging Markets. Then the spread rises during two months before stabilizing generally on a long horizon. The exchange rate impulse causes also a rise in the liquidity risk (Figure 20).

Figure 17.- Impulse response function of illiquidity and bid-ask spread to an increase in  $\Delta$ LIBOR

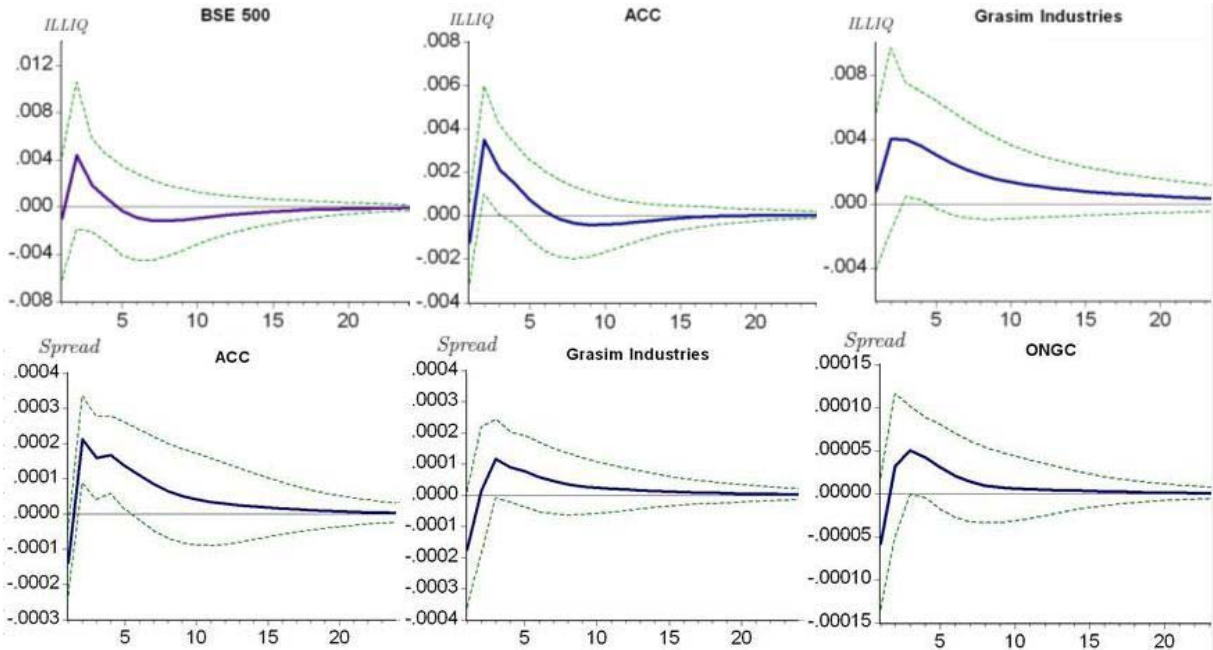
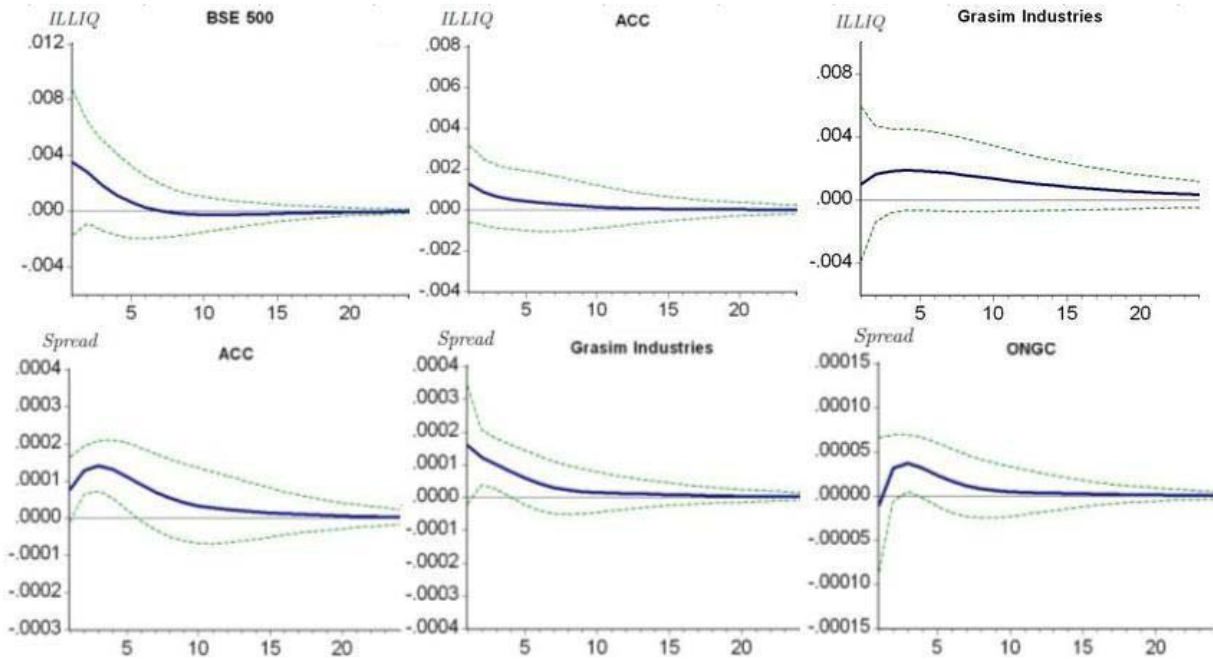


Figure 18.- Impulse response function of illiquidity and bid-ask spread to an increase in the CDS spread



The persistence of shocks on the BSE 500 index stands from 4 to 6 months, according to the risk observed. The persistence and the intensity of a specific shock fluctuate according to the index considered. However, on a whole, the response paths follow a similar pattern to the awaited direction.



Figure 19.- Impulse response function of illiquidity and bid-ask spread to a shock on the volatility of the S&P 500

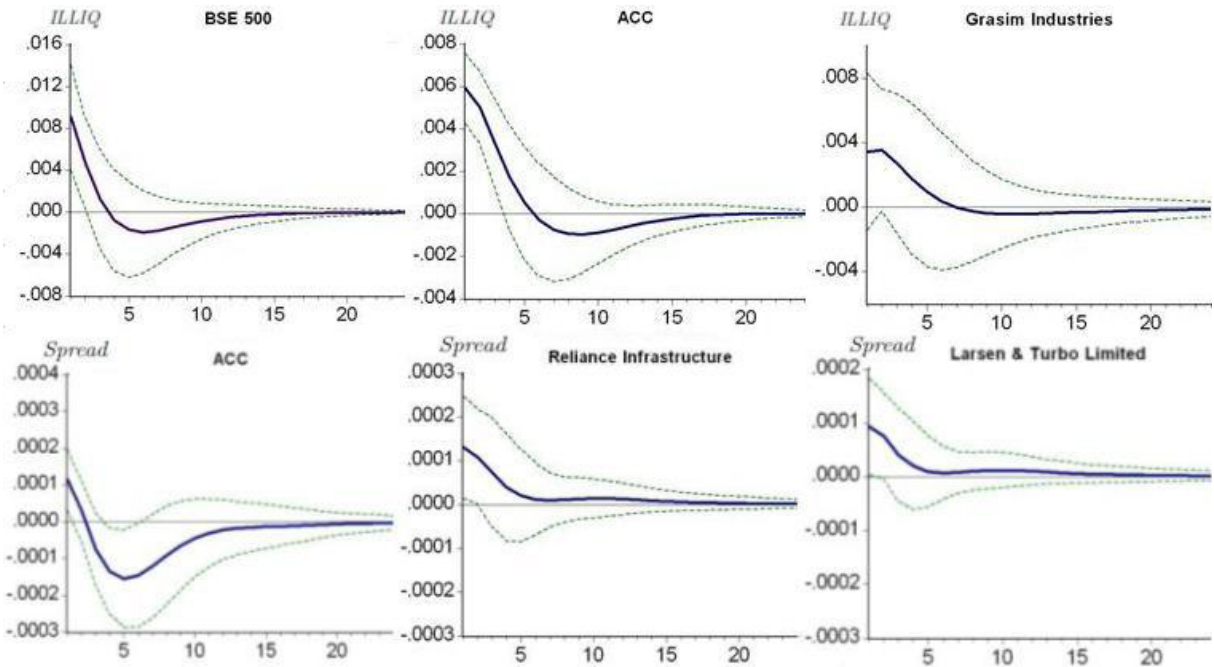
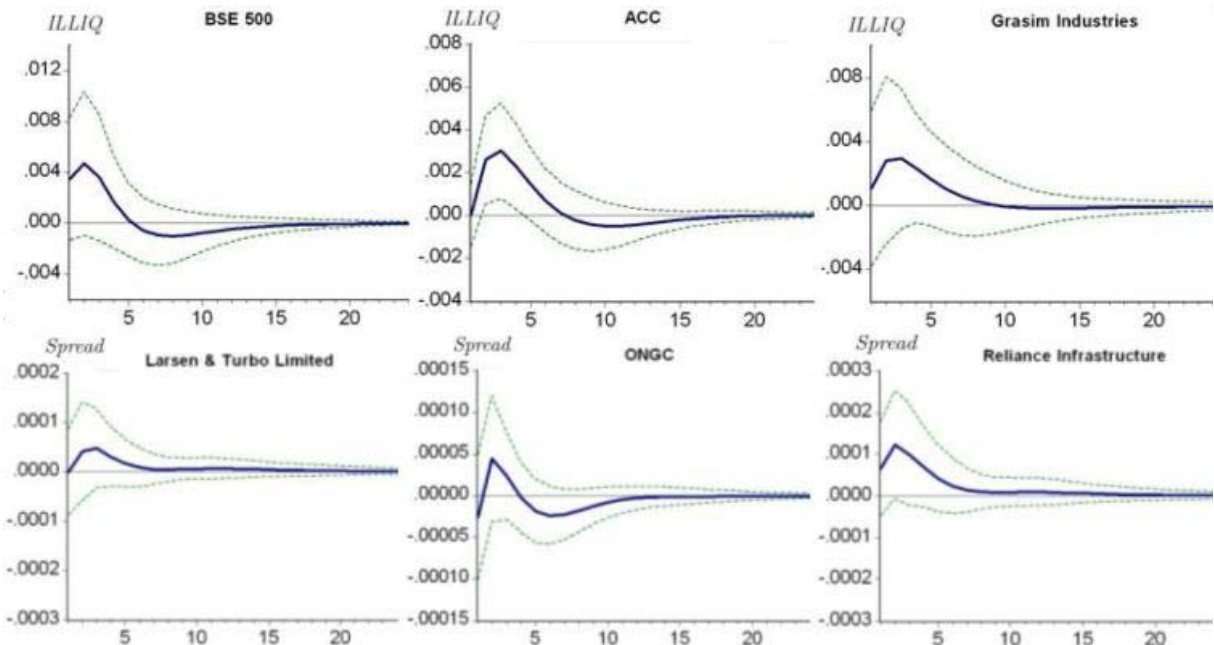


Figure 20.- Impulse response function of a illiquidity and bid-ask spread to a shock on the volatility of the exchange rate



Altogether, the impulse-response functions got out from the VAR models suggest that the perturbations identified in the Indian stock market from 2007 to 2008 were brought about by the

weakening of the U.S. financial system. More specifically, it is due to the deterioration of the U.S. financial institutions liquidity and solvency. These results play against the thesis of a financial decoupling between the US and Indian equity markets. It seems that there were linkages during the 2008 financial crisis, which we can explain by the interconnectedness between markets through investors' portfolio decisions. The crisis in the US markets has increased investors' risk aversion vis-à-vis all the stock markets, including the emerging markets, thereby implying substitutions among traded stocks and a preference for more secured securities (mainly public debts in the industrialized countries' bond markets).

To see whether the financial stress indexes on the U.S. market have had a stronger impact on both the volatility and the degree of illiquidity on the Indian stock markets during times of financial crisis than during the "normal" time, we estimate a time-varying coefficients model using the Kalman filter method. The estimated model is the following:

$$y_t = \alpha_t + X_t \beta_t + \varepsilon_t, \quad \beta_t - \beta = \phi(\beta_{t-1} - \beta) + u_t \tag{3}$$

Where the endogenous variable  $y$  is either the volatility or the liquidity variable and  $X$  is a vector of explanatory variables (among which the US financial stress indicators). We estimate a mean-reverting model by using the Kalman filter model for the BSE SENSEX and BSE 500 (for purpose of illustration<sup>3</sup>). In order to avoid too strong parameters variability – capturing the influence of market microstructures – the parameters stability is studied at a monthly frequency basis. As noted previously from the impulse response functions, shocks on daily time series show persistence effects for both the volatility and the illiquidity variables. A benefit from considering a monthly frequency is that it allows us introducing domestic variables as control variables (i.e. the differentials of inflation rates, short-term interest rates vis-à-vis the U.S. and the stock exchange capitalization-to-GDP ratio).

The evolution of the regression coefficients evolution shows that their size is higher during the sub-primes crisis period (Figures 21 through 34 in Appendix 1). We note that the filter adjusts relatively quickly from 2002 to 2006 despite some variations particularly in 2006 (the break on the Indian stock market is linked to the 2006 Bombay bombing). The strongest fluctuations take place after the first semester 2007 in all the regressions, resulting from the financial crisis contagion. Indeed, the regression coefficients increase from August to October 2007, pointing out a break in the shock transmission mechanism. Let us note also that over this period, all the estimates are positive, reaching their maximum value in September before they fall during the last quarter. More specifically, the estimates of the LIBOR-OIS spread, of the CDS along and of the S&P 500 volatility -

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<sup>3</sup> The results for the disaggregated indexes are not shown to save place but are available upon request to the authors.

are twice higher as those of the second semester 2007, and markedly bigger than those of the first semester 2007, just before the crisis.

The coefficients corresponding to the inflation rate differential and those related to the  $R^2$  index range up respectively to 0.00045 and 0.00031 for September 2008, against 0.000002 and 0.0001 for January. Let us note also – during the second semester 2008 - the significant increase in the coefficients of the exchange rate Dollar/Roupie (0.0012 in September 0.0004 against 0.0004 in January) and in the stock exchange capitalization-to-GDP ratio (0.00065 against 0.00042). Similar results are obtained for  $\sigma^2$ .

Finally, we note a significant increase of the coefficients value for ILLIQ (the liquidity index). Indeed, Figures 21 through 38 show a wider fluctuation of coefficients for the four explanatory variables during the second semester 2008, particularly in September.

We present two CUSUM tests in order to study the estimates stability. This parameters stability test is based on the cumulative sum of the recursive residuals (defined as a one step normalized prediction errors). For purpose of illustration we show these tests for the volatility indexes  $R^2$  and  $\sigma^2$  in order to detect an instability in the influence of the U.S. CDS (Credit Default Swaps) and of the S&P 500 volatility from 2007 to 2008.

Figures 39 to 41 show examples of these test outcomes with a 5% significance level. The sub-primes crisis effect is confirmed by the three graphs. One can check that the path leaves the corridor in September 2008 for the squared returns and the Amihud illiquidity ratio. As for the  $\sigma^2$  index, we note it leaves the corridor for the last quarter 2007. Eventually, we can define three phases for the evolution of coefficients estimated with the Kalman filter methodology. The first one ranges from 2002 to 2006, with coefficients that are fairly constants, an indication of the model stability. The second sequence concerns the period from the second semester 2007 to the third quarter 2008, with coefficients whose fluctuations are wider. At last, the third sequence occurs from September to December 2008, with a significant increase in the coefficients (particularly in September). Analyzing the graphs, the time of Lehman Brothers bankruptcy appears to be a key event explaining the Indian stocks market behavior during the crisis. In turn, the beginning of the sub-primes crisis all along the summer of 2008 seems to have had a very much weaker impact. All these conclusions are consistent with the VAR models result and with the stylized facts seen above.

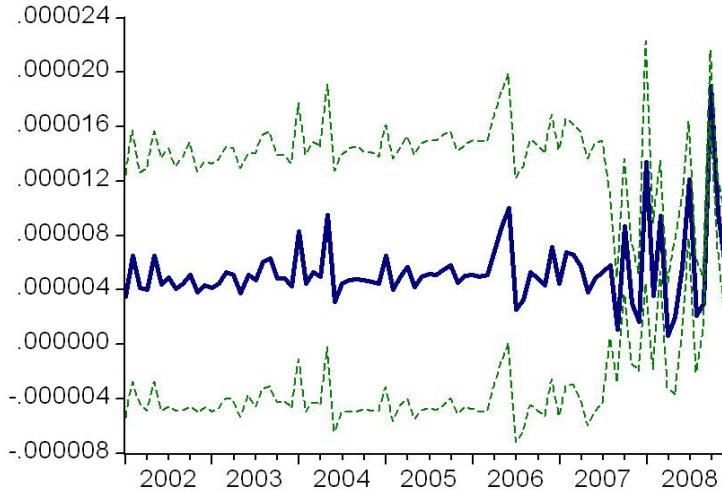


## **5.- Conclusion**

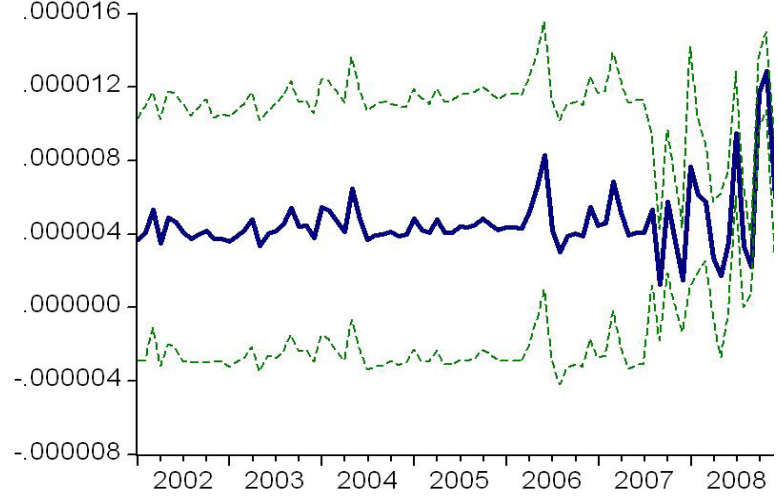
Did the subprime crisis have an impact in the Indian stock markets? This paper answer positively by providing evidence of a significant influence of some US financial stress indicators on both the volatility and illiquidity indicators of aggregate and disaggregated equity stocks. This finding is in accordance with a stylized fact observed in the emerging markets. Before the Lehman Brothers collapse, India benefited from a financial decoupling, as other emerging markets in Asia. But following the collapse the dichotomy between the financial stress in the US markets and the stress in the Indian markets disappeared. This is shown by both the stylized fact on the volatility and illiquidity indicators and by the Kalman filter analysis. The VAR analysis suggest that the impact was “structural” and not just temporary (due to the high persistence of shocks), which means that the observed drop in the Indian equities was not only the result of contagion behaviors but more generally of financial channels reflecting the important interconnectedness between the US and Indian Markets.

## Appendix. Graphs of Kalman filter analysis

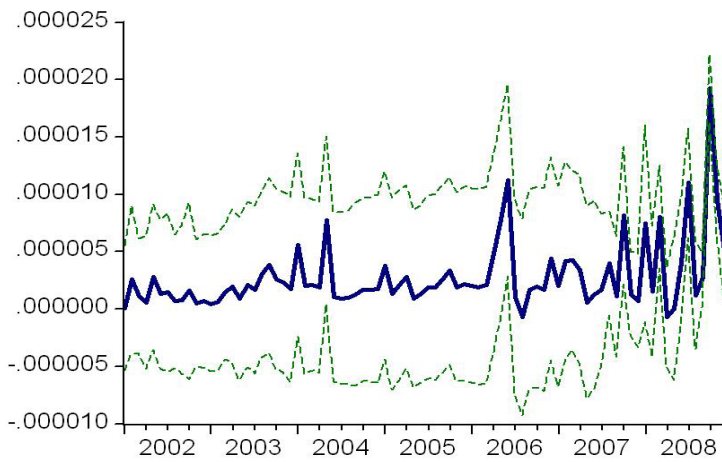
**Figure 21 .- Coefficient of spread LIBOR-OIS by Kalman filter**  
**Endogenous variable : Squared returns**



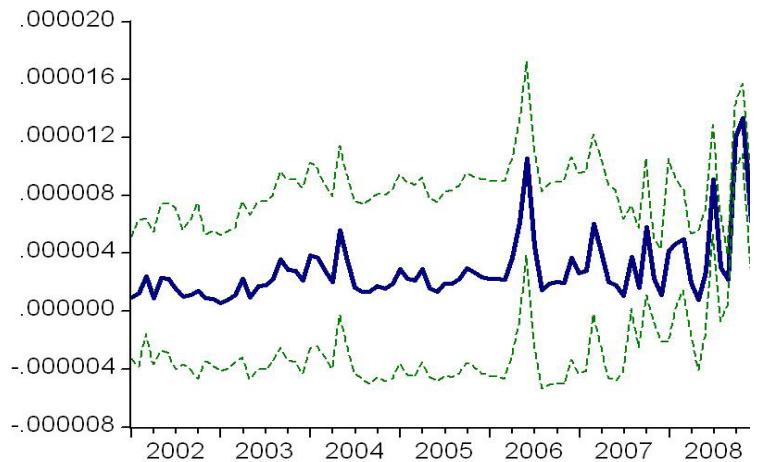
**Figure 22 .- Coefficient of spread LIBOR-OIS by Kalman filter**  
**Endogenous variable : conditional variance**



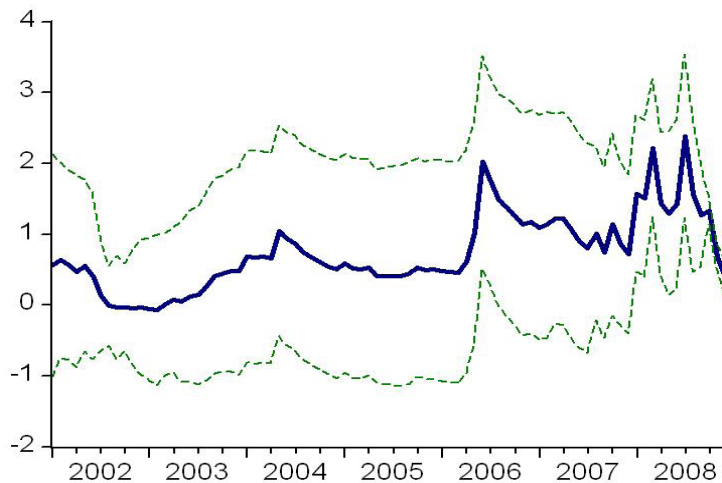
**Figure 23 .- Coefficient of CDS spread by Kalman filter**  
**Endogenous variable : Squared returns**



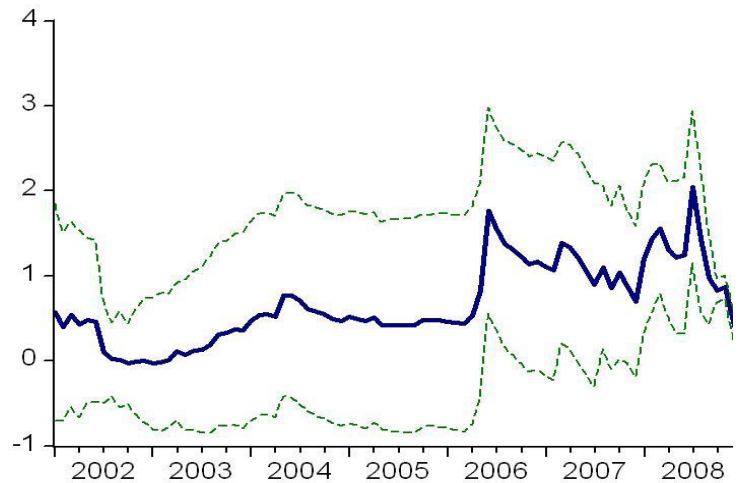
**Figure 24 .- Coefficient of CDS spread by Kalman filter**  
**Endogenous variable : conditional variance**



**Figure 25 .- Coefficient of the S&P 500 by Kalman filter**  
**Endogenous variable : Squared returns**

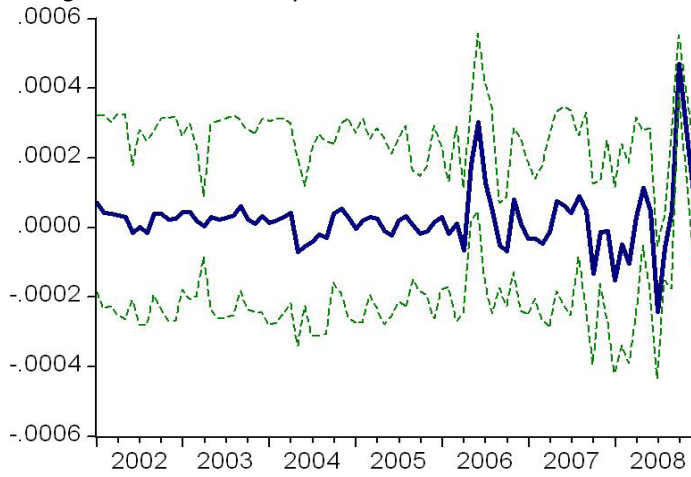


**Figure 26 .- Coefficient of the S&P 500 by Kalman filter**  
**Endogenous variable : conditional variance**



**Figure 28 .- Coefficient of the exchange rate by Kalman filter**

Figure 27.- Coefficient the exchange rate by Kalman filter  
Endogenous variable : Squared returns



Endogenous variable : conditional variance

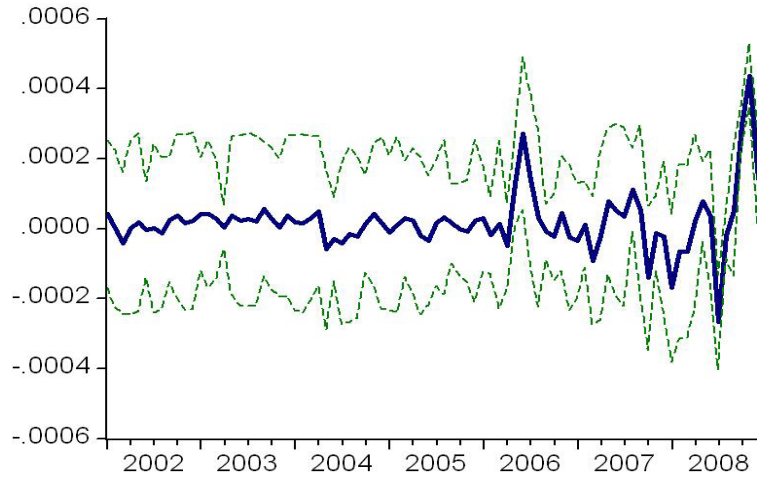


Figure 29.- Coefficient of inflation rate differential by Kalman filter - Endogenous variable : Squared returns

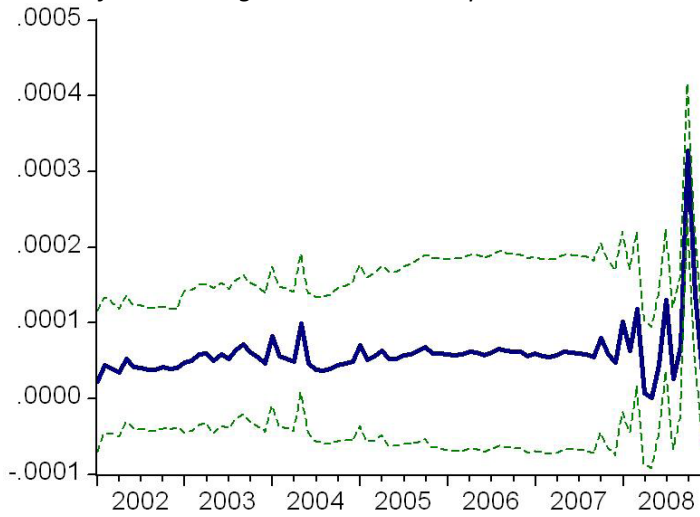


Figure 30.- Coefficient of inflation rate differential by Kalman filter - Endogenous variable : conditional variance

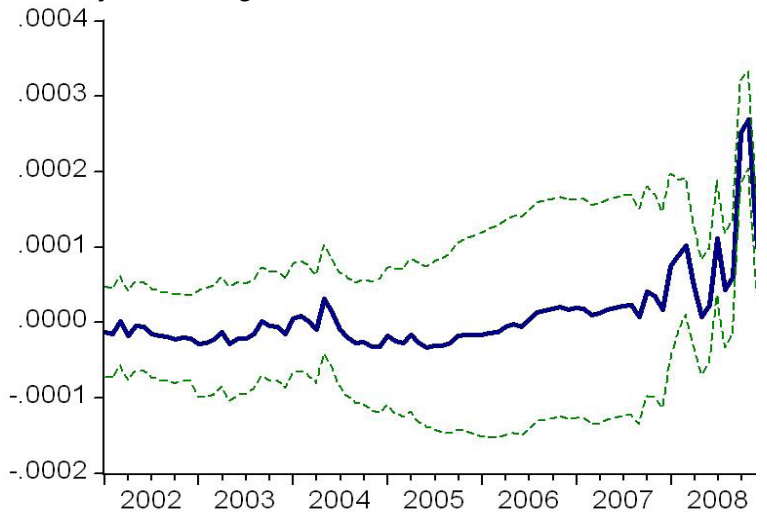


Figure 31.- Coefficient of interest rate differential by Kalman filter- Endogenous variable : Squared returns

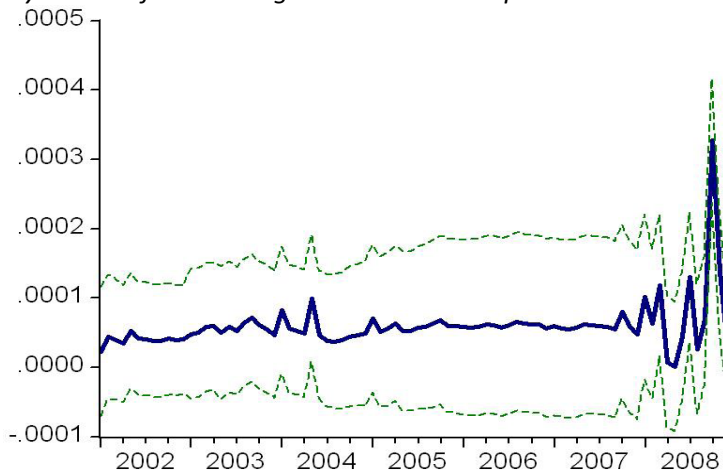


Figure 32.- Coefficient of interest rate differential by Kalman filter- Endogenous variable : conditional variance

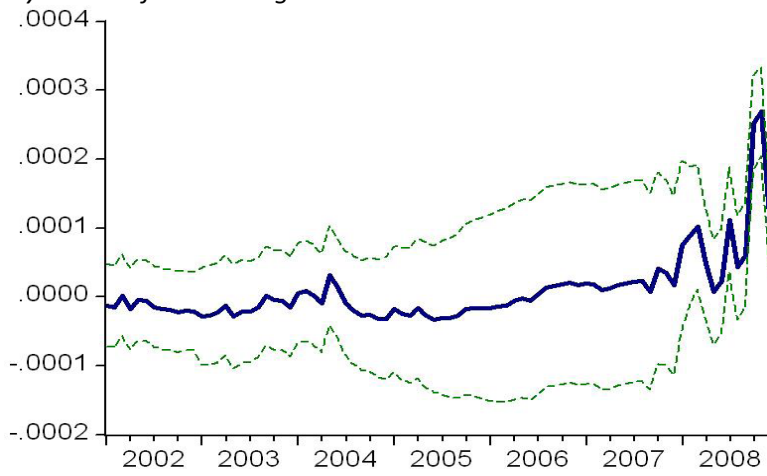


Figure 33 .- Coefficient stock market capitalization by Kalman filter -Endogenous variable : Squared returns

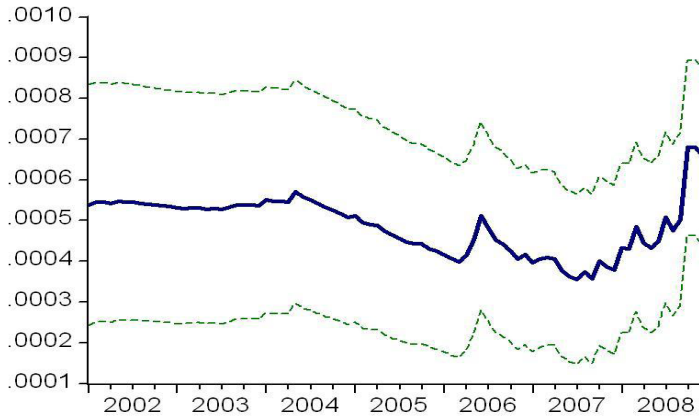


Figure 34 .- Coefficient of stock market capitalization by Kalman filter- Endogenous variable : conditional variance

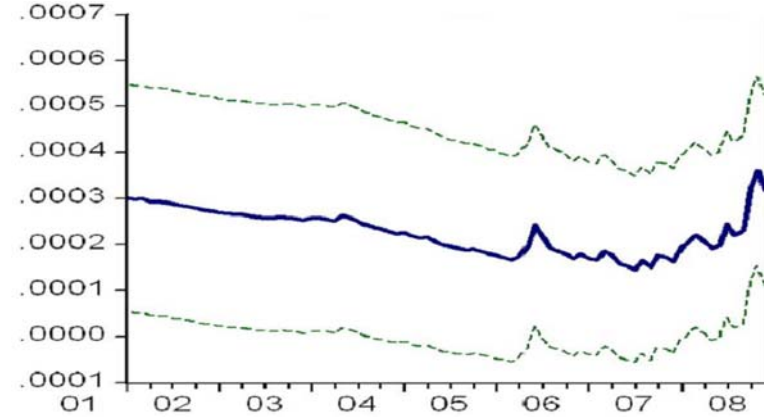


Figure 35 .- Coefficient LIBOR-OIS by Kalman filter - Endogenous variable : illiquidity ratio

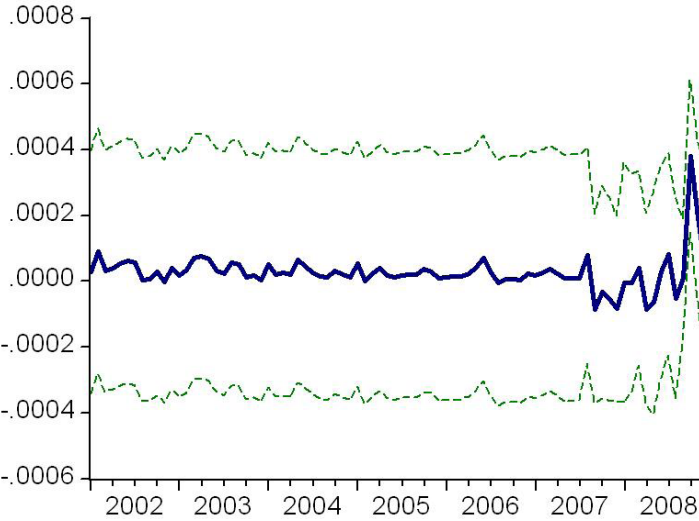


Figure 36 .- Coefficient of CDS spread by Kalman filter - Endogenous variable illiquidity ratio

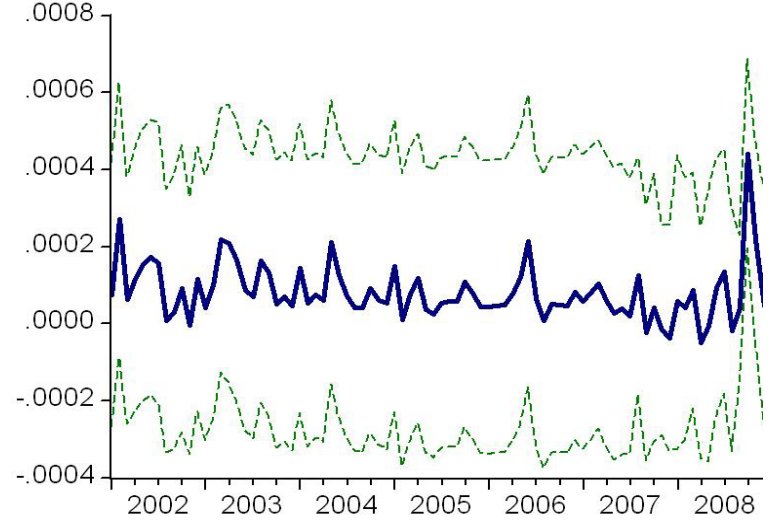


Figure 37 .- Coefficient of inflation rate differential by Kalman filter- Endogenous variable : illiquidity ratio

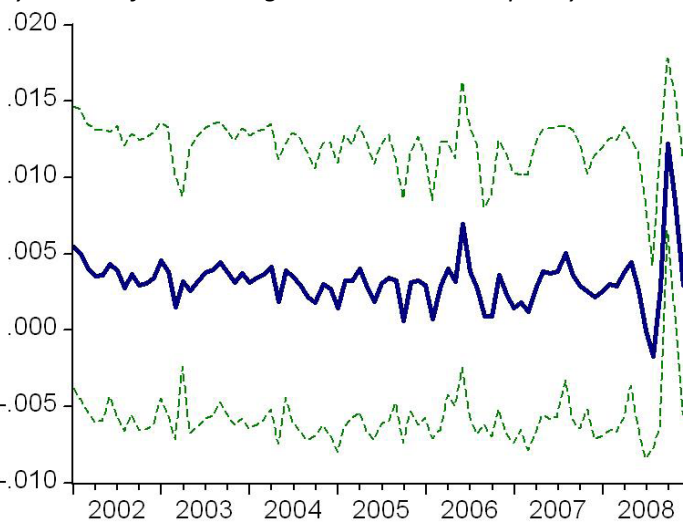


Figure 38.- Coefficient of interest rate differential by Kalman filter- Endogenous variable : illiquidity ratio

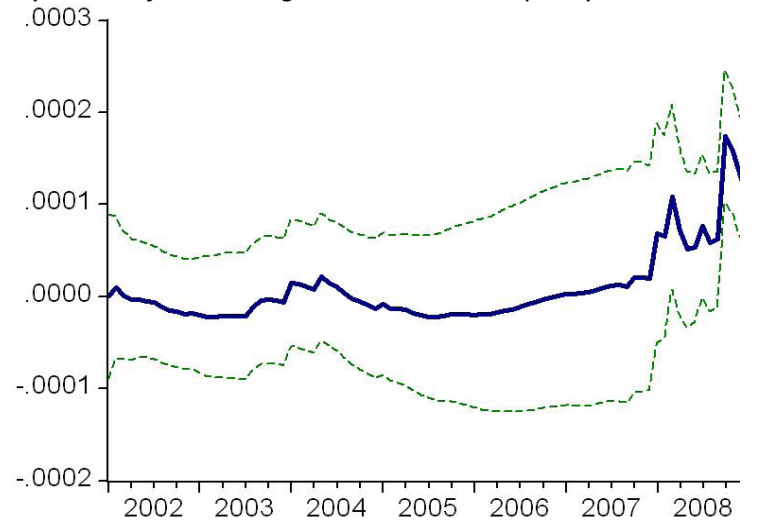




Figure 39.- CUSUM test for CDS  
 Endogenous variable : squared returns

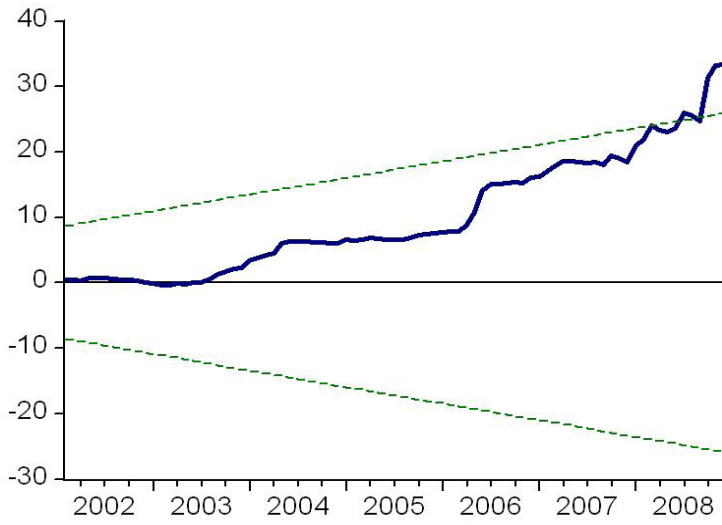


Figure 40.- CUSUM test for CDS  
 Endogenous variable conditional variance

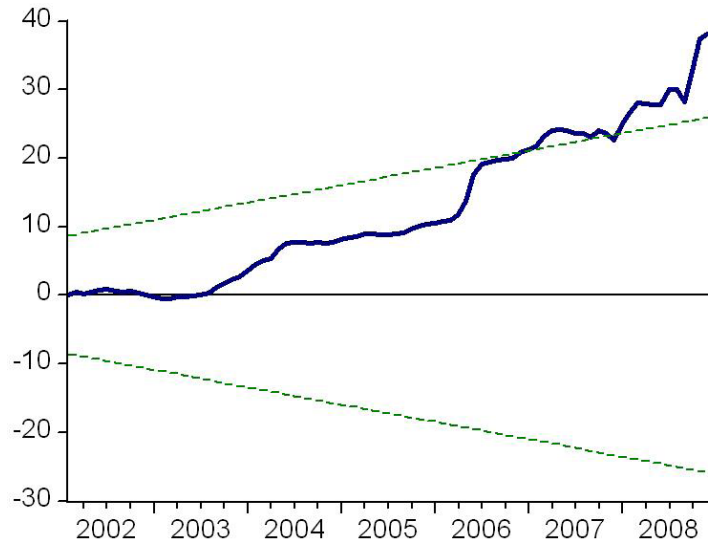
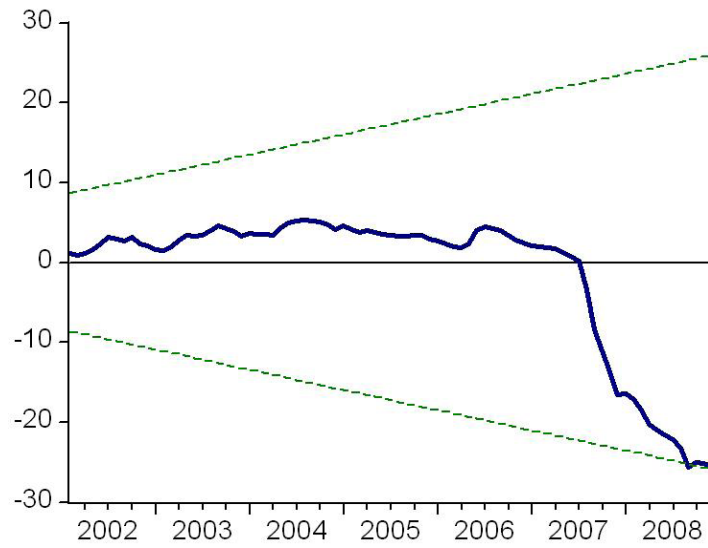


Figure 41.- CUSUM test for S&P 500 volatility  
 Endogenous variable: illiquidity ratio



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