Sector Volatility Shift modeling, Persistence and Dynamic Information flows

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Abstract:

The study explores three central issues: First, the impact of structural breaks on persistence of sector volatility; Second, the relationship between structural break identification method and persistence of volatility and third, the dynamic correlation structures of return volatility of sector pairs. Using weekly data spanning the period June 1994 through July 2014, three nested models of identifying structural breaks in unconditional volatility, break-augmented EGARCH model and cADCC model, the study evidences that volatility persistence significantly declines or is expunged once structural breaks are accounted for. Moreover, persistence is decreasing in the number of breaks hence depends on size, location and break-identification method. The study also document heterogeneous, time-varying and highly persistent co-movement structures in pairs of sector returns volatility which suggest cross-sector information flow. However, there is potential for risk diversification using lowly-correlated and decoupled sector pairs. Our results have important implications for pricing of contingent claims, asset pricing, volatility forecasting, cross-sector hedging and portfolio allocation decisions.

Key words: Volatility; Structural breaks; Persistence; Sectors; cADCC.
JEL classification: C22; G11; G12

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I. Introduction

The premise of international portfolio diversification is that pairs of national stock market returns have low positive or negative correlation. However, studies by Hatemi-J and Roca (2006), Goetzmann et al (2005), and Gilmore and McManuc, (2002) show that global correlations of national stock market returns have increased over time partially due to liberalization and deregulation in most countries, integration of global financial markets, rapid transmission of information across global financial markets and synchronization of monetary and fiscal policies among countries in monetary and economic union. There trends have resulted in increased erosion of the benefits of international portfolio diversification.

The decline in international portfolio diversification has led investors to scour for new and alternative investment vehicles that offer portfolio diversification benefits. This has elicited formation of sector-based portfolios in form of equity traded funds (ETFs) and investible sector indices (ISI). We study the sector returns for three primary reasons. First, Campbell et al. (2001) find that the incessant increase in idiosyncratic volatility of sector and firm-level returns has enfeebled the ability of the market model to provide explanatory power on volatility of firm and sector returns. Therefore, there is need to study of volatility at a more disaggregated level. However, Ross et al (2013) further argues that investors can better estimate a firm's systematic risk by including the entire industry. This is because risk estimations of a single stock are subject to large, random variations relative to industry-wide estimates. The error in estimation of systematic risk of a firm is much higher than the error for a portfolio of securities. This argument suggests using sector volatility may produce better risk modeling estimations for risk management and investment decisions. Second, the increasing popularity of sector ETFs and ISI requires a more disaggregated volatility modeling to capture risk-return dynamic at sector level.

This is even more compelling since sector-index investing affords investors instant diversification benefit in addition to reduction in trading and functional costs of managing an index portfolio. Ferreira and Ferreira (2006), Cavaglia, Brightman and Aked (2000) and Schwob (2000) has found increasing importance of industrial or sector factors (relative to country factors) in explaining variation of global portfolio returns. A recent study by Phylaktis and Xia (2006) shows that in recent years, sector effects have largely smoothed out the national stock market effects while Roll (1992) shows that the industrial structure of the domestic economy is critical in explaining the correlations among national stock index returns. Third, the theory of home-bias documented by various authors[2] shows that despite the purported benefit of international diversification, investors have higher proclivity to anomalously allocate more capital in domestic financial assets than in foreign financial markets. It is therefore crucial to analyze and understand the dynamics of domestic sectors markets in asset allocation decisions.

In this study, we attempt to answer a number of questions: First, do sector returns volatility exhibit persistence? The persistence of volatility embodies the extent to which transient return shocks can trigger fundamental and enduring effects on future in volatility patterns. Such shock increases the predictability of volatility over many periods in future. This has significant implications. Lamoureux and Lastrapes (1990) show that the pricing of contingent claims is incalculably influenced by degree of permanence of shocks with transitory shocks generating less significant effect on the pricing of derivatives. Persistence of asset return volatility implies that changes in assets expected risk and return tradeoff (and hence investment opportunity set) may vary with business cycles (Poon and Granger, 2003; Ang et al, 2006). The asset pricing model of Poterber and Summers (1986) also shows that the intrinsic value of a

[2] See for example French and Poterba (1991), Tessar and Werner (1995), Coval and Moskowitz (1999), Obsfeld and Rogoff (2000), Van and Veldkamp (2005) and Ferreira and Matos (2008) *inter alia*.

financial assets is inversely related to expected persistence of volatility. Ergo, accurate modeling and estimation of sector returns volatility persistence affect pricing of sector ETFs and ISI instruments. Volatility persistence affects adoption of suitable policies. A negative sector return shock that impacts non-stationary sector index or a positive volatility shock that affects stationary, mean-reverting conditional volatility requires an aggressive policy due to permanent effects the shocks is likely to generate.

Second, do sectors returns and volatility share common structural breaks? The theory of sector rotation investment strategy intimates that different domestic sectors exhibit different risk-return trade-off in different business cycles. Kraus (2001) and Brooks and Negro (2004) show that all sectors in equity markets do not respond homogeneously to local and common shocks. Would domestic sectors share mutual structural break points? The occurrence of sectoral structural breaks approximately at the same point may be indicative of correlated trading activities among investors. This is a harbinger of herding behavior.

Third, how do the breaks affect persistence of volatility at sector level? Domestic economic sectors are sporadically susceptible to abrupt "large" shocks which can instigate disruptions in the unconditional variance and subsequently affect persistence of conditional volatility. Campbell and MacKinlay (1997) argue that it is both logically inconsistent and statistically inefficient to use volatility measures that are based on the conjecture of constant volatility over certain period when in fact, the resulting series is not time-invariant. Stărică et al. (2005) also shows that long-horizon forecasts of stock return volatility based on GARCH(1,1) models which ignores disrupting structural breaks (assumes constant unconditional variance) yield inferior forecast results relative to GARCH (1,1) models which account for structural breaks in the unconditional variance of stock returns.

Fourth, how does structural break identification method (through number of breaks) affect persistence of volatility? A recent simulation study by Výrost, Baumöhl and Lyócsa (2011) shows that the estimated persistence in volatility depends inversely on the number of breakpoints in volatility. This suggests that persistence of volatility may be directly related to chosen volatility break-detection tests since different tests yield different number, sizes and locations of structural breaks. This issue has not been empirically investigated in past studies, more so for sector returns.

Lastly, is there information flow among sector returns? Ross (1989) argues that volatility spillover is a measure of information flow among assets. The investors' sector-based allocation and diversification decisions require insight on information flow and linkage among the sector indices. Hassan and Malik (2007) find significant shock and volatility transmission among different sectors, suggesting that investors ought to understand the linkage and mutual information among various sectors to evaluate the potential for cross-sector hedging and optimal portfolio allocation decisions. More importantly, negative or positive feedback mechanism among the sectors will ultimately affect the overall economy (Ewing, 2002) and performance of portfolios.

There is a rich literature on the information flow across national stock markets but a dearth of studies focusing on the role of information flow and other dynamics across diverse domestic market sectors (Wang et al., 2005). The few notable studies on sector return or return volatility dynamics are McMillan and Wohar (2011) for UK sectors and Cagli, Mandaci and Kahyaoğlu (2011) for Turkish sectors. Malik and Farooq (2004) and Hassan and Malik (2007) focus on US sector returns. Malik and Farooq (2004) studies structural breaks and volatility persistence of five major Dow Jones sectors while Hassan and Malik (2007) employs multivariate GARCH to investigate sector volatility transmission. The common finding of the sector-based studies (except Hassan and Malik, 2007) and other studies on structural breaks and persistence of volatility[3] is that accounting for breaks in unconditional volatility significantly reduces persistence of volatility. One aspect the past studies fail to investigate is relationship between the number of breaks and volatility persistence, an issue at the heart of this study. Another unique aspect of our study is data. Our study utilizes returns of ten major US economic sectors, spanning a period of twenty years. We use investable sector indices which cover up to 99% of the free float adjusted market capitalization of US equity market. The sector indices capture over 2400, small, mid and large cap stocks. The indices are more liquid relative to non-investable sector indices.

The rest of the paper is organized as follows: Section II details the source of data, data characteristics and preliminary model specification tests. Section III explains econometric methodology. Section IV discusses empirical evidence while section V concludes.

II. Data sources and characteristic

Our study focuses on the ten most popular economic sectors in U.S. We collect weekly sector index data from Morgan Stanly Capital International (MSCI)[4]. The nominal sector returns are computed as log difference of sector indices. We abbreviate the sector index and real sector returns[5] as CDI for consumer durables, CSI for consumer staples, EGY for energy, FIN for financial, HCI for health care, IND for industrial, TEC for technology, MAT for materials, UTL

[3] See for example Hendry (1986), Lamoureux and Lastrapes (1990), Mikosch and Stărică (2004) and Hillebrand (2005)

[4] See the data from MSCI website http://www.msci.com/products/indices/sector/usa_imi_sector_indexes/ Accessed 08/05/2014

[5] We collect the monthly consumer price index (CPI) and convert it to weekly index. We deflate the nominal sector returns by the inflation rate (1+growth rate in CPI). We use real sector returns in our analysis since investors are interested in real returns. Moreover, we do not want our results be contaminated by breaks and volatility persistence which may be inherent in inflation rate.

for utilities and TEL for telecommunication economic sectors. With exception of TEL sector, the weekly data spans the period 06/1994 through 07/2014, accounting for 1049 weekly returns. The TEL sector data is available from 12/1998 through 07/2014, accounting for 814 weekly returns.

We use weekly prices to avoid the problems of non-synchronous trading, bid-ask spread and non-trading more commonly associated with daily prices. This is consistent with Lo (1991) and Chen, Firth and Rui (2001). The use of the MSCI sector data is motivated by three factors: First, the sector indices are investable which makes them liquid unlike conventional non-investable indices. Second, the ten investable market sector indices (ISI) are representative of the US equity market as they cover up to 99% of the free float adjusted market capitalization of US equity market. Moreover, the ISI sector indices are derived from the broad MSCI USA investable market indices (IMI) which consists of over 2400, small, mid and large cap stocks. As such, they don't have selection bias of small or large cap US stocks. The consistent construction methodology of the indices makes them suitable to carry out comparative analysis of dynamic behavior of the ten sectors

III. Econometric methodology

Past studies[6] on structural breaks in unconditional volatility employ iterative cumulative sum of squares (ICSS) algorithm developed by Inclan and Tiao (1994). The formulation of ICSS algorithm is as follows: If ε is identically and independently distributed series of residuals with zero mean and unknown unconditional variance σ_t^2 [$\varepsilon_t \sim iid$ $\mathrm{N}(0,\sigma^2)$]. Let T be the number of observations, j an interval within T, σ_j^2 the variance in each interval and N_T the number of

[6] See for example, Malik and Farooq (2004), Ewing (2002), Ewing and Malik (2010), McMillan and Wohar (2011)

variances in T observations. We can present the number of structural break points as $1 < k_1 < k_2 < \ldots. < k_{N_T} < T$ where N_T is number of intervals over which variance is computed.

Let C_k be cumulative sum of squares of residuals used to identify the number of shifts (breaks) and the break point, k.

$$C_k = \sum_{t=1}^{k} \varepsilon_t^2, \text{ where } k = 1,2,\ldots\ldots,T \tag{1}$$

Let D_k represent the ICSS critical statistical value for the null hypothesis of homoscedasticity over interval N_T

$$D_k = \frac{C_k}{C_T} - \frac{k}{T}, \quad k = 1,2,\ldots\ldots T \tag{2}$$

In equation 2, c_T is the total sum of squares from the whole sample period consisting of T observations. The critical values of ICSS test are derived from distribution of D_k. The critical value, D_k, is plotted against k to identify breaks in unconditional variances. If there are no structural breaks, the graphed line will horizontally fluctuate around zero. Inclan and Tiao (1994) established D_k as 1.358 at 95 percent confidence level. Under the assumption that $\varepsilon_t \sim iid\ \mathrm{N}(0,\sigma^2)$, the asymptotic distribution of *ICSS* takes the following formulation

$ICSS \Rightarrow \max_k \sqrt{(T/2)}|D_k|$. The function $\sqrt{T/2}$ standardizes the distribution, while k^* is the value which breaches the upper and lower limits of the critical value; ± 1.358. The symbol $\Rightarrow$ exemplifies weak convergence of probability measures of the test. When upper and lower limits are breached, then, k^* represents the structural break point of unconditional variance. A graphical plot of D_k against k will indicates all zigs and zags and all breaches of the thresholds. The breaches, k^*, are equal to endogenous search and identification of multiple shifts in unconditional variance.

The *ICSS* test of identifying structural break in volatility is fraught with three main flaws. First, Rapach and Strauss (2005) show that in case of serial correlation in residuals, *ICSS* test misrepresents the size of structural break in unconditional variances. Therefore, a new method is necessary to account for serial dependence of residuals. Second, the test is premised on the null hypothesis of homoscedasticity over variance interval, N_T. Rapach and Strauss, 2008 and Sanso et al., (2004) show upward bias in estimation of *ICSS* statistic whenever returns follow GARCH process. Our time series returns are characterized by excess kurtosis (fat-tailed" Leptokurtic distributions) and heteroskedasticity of residuals Third, the assumption of $\varepsilon_t \sim iid\ \mathrm{N}(0,\sigma^2)$ is inappropriate since residuals are non-mesokurtic. Andreou and Ghysels (2002) document that these assumptions cause overestimation of the number of breaks using the *ICSS* test. Table 1 results show non-normal distributions of sector returns, serial correlation, heteroskedasticity and "fat-tailed" Leptokurtic distribution. Therefore, *ICSS* test alone may not be apropos for this study. To this end, we utilize *IT*, Kappa-1 (*k1*) and Kappa-2 (*k2*) tests of Sanso et al. (2004). These tests amend the three weaknesses of *I*CSS but are nested on the *ICSS* test.

The *k1* test corrects for normal distribution of residuals assumption and generalizes the *ICSS* test. The modified or generalized *ICSS* test is denoted as *IT* test. Specifically, under conditions of $\varepsilon_t \sim iid\ \mathrm{N}(0,\sigma^2)$ and $\varepsilon_t^4 \equiv \eta_4 < \infty$, the asymptotic distribution of *IT* would be as follows:

$$IT \Rightarrow \sqrt{\frac{\eta_4 - \sigma^4}{2\sigma^4}} \sup_r |W^*(r)| \qquad (3)$$

where $\Rightarrow$ typifies weak convergence of probability measures associated with *k1* test. $W^*(r) \equiv Wr - rW(1)$ is a Brownian bridge while *W(r)* is the archetypal Brownian motion. Since *IT* assumes normal distribution, then, kurtosis is equal to $\eta_4 = 3\sigma^4$. However, in presence of leptokurtic distribution, $\eta_4 > 3\sigma^4$. The leptokurtic distribution of sector returns, which is a predominant feature of most financial time series, means that *IT* test will report high incidences of rejecting the null hypothesis of homoscedasticity. Sanso et al (2004) developed the *k1* test by adjusting the generalized *IT* test. The incorporation of leptokurtic and non-normal distribution in *k1* test made the normal distribution and homoscedastic assumptions under *IT* test nuisance parameters. The use of Brownian Bridge to establish maximum critical values of can also induce numerous distortions. Sanso et al (2004) removed the nuisance parameter and formulated the *k1* test (under the assumption of *iid* random variables) as follows

$$k1 = \underset{k}{Sup} \left| T^{-1/2} B_k \right| \text{ or } k1 \Rightarrow \sup_r |W^*(r)| \qquad (4)$$

Where $B_k = \dfrac{C_k - \frac{k}{T} C_T}{\sqrt{\hat{\eta}_4 - \hat{\sigma}^4}}$, $\hat{\eta}_4 = T^{-1} \sum_{t=1}^{T} \varepsilon_1^4$, $\hat{\sigma}^4 = T^{-1} C_T$ and $k = 1,2,.....,T$

The asymptotic distribution of *k1* [$k1 \Rightarrow \sup_r |W^*(r)|$] is premised on the condition that $\varepsilon_t \sim iid$

and $E(S_t^4 \equiv \eta_4 < \infty$

The assumption of *iid* random variables with zero mean significantly reduces the power of generalized *IT* and *k1* tests in presence of conditional heteroskedasticity (Bollerslev et al.1992). The *k2* test corrects for non-normal distribution of returns and persistence nature of conditional volatility in presence of heteroskedastic disturbances. These features characterize the sector returns according to table 1. Sanso et al (2004) assumed, under some conditions[7] that the residuals are sequentially and randomly generated such that $\{\varepsilon_t\}_{t=1}^{\infty}$. The *k2* test is formulated is as follows:

$$k_2 = \underset{k}{Sup}\left|T^{-1/2}G_k\right| \tag{5}$$

Where $G_k = \hat{\omega}_4^{-0.5}\left(C_k - \frac{k}{T}C_T\right)$ and $\hat{\omega}_4$ is a consistent estimator of ω_4. $\hat{\omega}_4$ can be estimated non-parametrically as follows

$$\hat{\omega}_4 = \frac{1}{T}\sum_{t=1}^{T}\left(\varepsilon_t^2 - \hat{\sigma}^2\right)^2 + \frac{2}{T}\sum_{t=1}^{m}\omega(\ell, m)\sum_{t=\ell+1}^{T}\left(\varepsilon_t^2 - \hat{\sigma}^2\right)\left(\varepsilon_t^2 - \hat{\sigma}^2\right) \tag{6}$$

In equation 6, $\omega(\ell, m) = 1 - \frac{\ell}{(m+1)}$. Additionally, if $\xi_t = \varepsilon_t^2 - \hat{\sigma}^2$, then $\hat{\omega}_4 \rightarrow E(\xi^2) = \eta_4 - \sigma^4$ [8]

In summary, this study uses the three methods (*IT*, *k1* and *k2*) to identify the structural breaks in unconditional volatility.

Our next step is to model persistence of volatility. Engle and Patton (2001) outline the features of a good volatility model: First, it should capture pronounced persistence and mean reversion in volatility. Second, it should capture asymmetry (leverage effects) since positive and negative innovations may affect conditional volatility differently. (Black, 1976). Third, it should account for the possibility of exogenous or pre-determined variables influencing volatility. To this end, we use the exponential generalized conditional heteroskedasticity (EGARCH) model of

[7] See Sanso et al (2004) for more information

[8] In derivation of *K1* and *K2,* the bandwidth selection is based on Newey-West methodology.

Nelson (1991) which captures the first two features[9]. In addition to the three features, Cumby, Figlewski and Hasbrouck (1993), and Chen, Firth and Rui (2001) enumerate another benefit of EGARCH model: the use of log in EGARCH model ensures that the ARCH and GARCH coefficients are not restricted to positivity. The base EGARCH model is as follows:

$$\ln \sigma_t^2 = \lambda + \alpha \left| \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} \right| + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \beta \ln \sigma_{t-1}^2 \tag{7}$$

In equation 7, coefficient λ estimates unconditional volatility while coefficient α captures the impact of size of a past standardized shock on current conditional volatility. The coefficient γ measures the leverage (sign of the shock) effects while a statistically significant coefficient β indicates persistence of volatility. The closer β is to unity, the higher the persistence of conditional volatility. The coefficients α and γ should be significantly positive and negative respectively for the model to be stationary

Hendry (1986), Lamoureux and Lastrapes (1990), Mikosch and Stărică (2004) and Hillebrand (2005) find upward bias in estimation of β when structural breaks in unconditional variance are not incorporated in GARCH model. This is equivalent to omission of variable bias. Therefore, to generate reliable and more accurate β estimates, and to capture the third feature of a good volatility model as enshrined by Engle and Patton (2001), we augment equation 7 with structural breaks as follows

$$\ln \sigma_t^2 = \lambda + \alpha \left| \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} \right| + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \beta \ln \sigma_{t-1}^2 + \sum_{i=1}^{n} dnDUM_{n,p} \tag{8}$$

[9] In adopting the EGARCH model, we also conducted the sign bias test proposed by Engle and Ng (1993) to ensure correct model specification where potential asymmetric effects are incorporated in our modeling.

In equation 8, $DUM_{n,p}$ represents dummy variables that takes a value of one from the structural break date onward and zero otherwise. This is implemented for each structural break test model, p where $p=IT$, $k1$ and $k2$. Contrary to prior studies, we use structural breaks generated by each of the three tests and not just *IT* (ICSS). Each of the three tests generates different number and oftentimes, location of breaks. Therefore, it is possible that persistence of volatility depends on the location, size and number of structural breaks. The coefficients of equations 7 and 8 models are estimated by maximizing the log-likelihood using the Berndt et al (1974) algorithm. We also use generalized error distribution (GED) to capture "fat tailed" leptokurtic distribution of sector returns.

IV. Empirical Results

We first analyze descriptive statistics and preliminary model specification tests. We normalize standard deviation (S.D) by average returns to derive coefficient of variation (C.V). The CSI (TEL) sector presents the lowest (highest) risk per unit of return. While the TEC sector returns present the highest risk, it is in the TEL sector where investors bear the highest risk to generate one unit of returns (C.V=103.595).

INSERT TABLE 1 AROUND HERE

All the sector returns are negatively skewed indicating higher probability of losses in unfavorable market conditions. Moreover sector returns exhibit leptokurtic, fat-tailed distribution (excess kurtosis), signaling a higher probability of obtaining an extreme return outcome than a normal return outcome. We test for normal distribution of return using a robust Jacque-Bera (RJB) test of Gel and Gastwirth (2008) which controls for outliers. Again, all sector returns exhibit non-normal distributions, notably driven by excess kurtosis and negative skewness. The returns also exhibit non-constant variance (heteroskedasticity) since the ARCH test of Engle (1982) and LB^2 of Ljung and Box (1978) are firmly rejected. The LB tests also suggest presence of serial dependence in returns. The interesting feature of this analysis is the heterogeneity of distributional characteristics of sector returns which may point to inherent dissimilarities. Our econometric modeling enable us to capture the identified return distributional features namely, heteroskedasticity, non-normal distribution, leptokurtic distribution and autocorrelations.

Persistence of variance: Evidence sans structural breaks

We investigate persistence of volatility using the baseline EGARCH model captured in equation 7. We analyze and assemble the econometric evidence in table 2. There are three key pieces of evidence. First, the persistence of volatility is high and significant as shown by coefficient estimate, β. With exception of HCI sector (β=0.877), all sectors register persistence higher than 0.9 with the TEC recording the highest persistence at 0.979. The half-life, which measures the number of periods a shock takes to reduce to half its original size, also varies across the sectors. This suggests that different sectors synthesize the impact of a shock at different speeds. Half-life is increasing in the degree of volatility persistence hence HCI (TEC) has the shortest (longest) half-life. It will take as long (short) as 32.52 (5.3) weeks in TEC (HCI) sector for a shock to shrink to its original size.

INSERT TABLE 2 AROUND HERE

The high persistence of volatility may be indicative of inefficient market otherwise efficient market ought to have low volatility drift as past conditional volatility is fully, rapidly and accurately incorporated in current conditional volatility. Second, the size and leverage (asymmetry) coefficients (α and γ respectively), are strongly significant with the correct signs.

This suggests that negative exogenous shocks to sector returns have more destabilizing effects on current conditional volatility relative to positive shock of the similar magnitude. This has significant policy consequences. Specifically, if the conditional variance is mean reverting, negative shocks do not require strong policy measures since variance will ultimately revert to its original trend in future. However, a negative shock affecting non-stationary conditional variance of sector returns will inflict permanent effects and will require strong policy measures to mitigate explosion. Third, the model specification tests confirm homoscedastic or constant variance of residuals (insignificant ARCH and LB^2 statistics) and zero serial correlation of residuals as attested by insignificant LB statistic. The model is also stationary since for all sectors, β is greater α, suggesting that large shocks to each sector do not cause major revisions in future conditional volatility. Our results in table 2 provide evidence of significant heterogeneity in persistence of volatility, leverage and size despite the fact that the sectors belong to the same domestic market.

Next, we test for existence of structural breaks in unconditional volatility and the break point using *IT*, *k1* and *k2* methods. The results of number of structural breaks and break dates are presented in table 2. We empirically confirm that *IT (k2)* method generates the highest (lowest) number of breaks for each sector. Moreover, different sectors have heterogeneous number and points of breaks suggesting that the sectors do not homogeneously and simultaneously respond to external shocks.

INSERT TABLE 3 AROUND HERE

Lastly, all sectors have one or more breaks during the years 2007, 2008 and 2009 which marked the heightened convulsions of financial markets triggered by the global financial crisis

(GFC) of 2007-2008. Moreover, the boom and bust in technology sector between mid-1990s and early 2000s seems to have triggered breaks around 08/1998 and 03/2003. Generally, the identified breaks coincide with major financial or economic disruptions in U.S

After testing for presence of structural breaks and the corresponding break points, we assess how structural breaks affects persistence of volatility. The results in table 3 do not account for structural breaks in unconditional volatility. We use equation 8 to incorporate structural breaks in estimation of persistence parameters. Our investigation proceeds as follows: We estimate all the coefficients of equation 8 using three structural break test methods videlicet *IT*, *k1* and *k2*. We test whether the structural break dummies are jointly significant in influencing conditional volatility. Lastly, we compute the likelihood ratio (LR) to test whether the breaks-augmented EGARCH model in equation 8 (unrestricted model) fits data better than EGARCH model in equation 7 starved of breaks (restricted model). Our results are offered in table 4.

INSERT TABLE 4 AROUND HERE

We document significant decline in persistence of volatility in all sectors using all structural break tests. However, one notable thing is the severe decline in persistence of volatility under *IT* method where six sectors (FIN, HCI, MAT, TEC, UTL, and TEL), register insignificant β insignificant after accounting for structural breaks. It is worth noting that *IT* method generated the highest number of breaks for each sector. Among the β parameters that remain significant, CDI (using *IT* method) registered the highest decline in persistence (from 0.966 to 0.395) of 145% while TEL sector (using *K1* method) recorded the lowest decline (from 0.971 to 0.957) of 1.46%. The leverage effect coefficient estimate, γ, remains statistically significant implying that negative news still exerts more destabilizing effects on current conditional volatility relative to positive news even after incorporating the breaks. The structural breaks ostensibly reduced the impact of the size of the shock on conditional volatility as the statistical significance of the coefficients, α either disappears or is weakened. This is not uncommon since breaks are themselves shocks which, if omitted, will result in a significant α. The structural break dummies are jointly significant (F-dummy statistics) under at least one of the break tests; hence they exert significant impact on conditional volatility of sector returns. One notable piece of evidence is that the dummies exhibit stronger joint significance under either *k1* or *k2* tests which apparently yielded fewer structural breaks. This could suggest that the *IT* method either overestimate the scale and number of breaks or signals spurious breaks. Lastly, by consistently reporting statistically significant Likelihood Ratio (LR), we provide supporting evidence that incorporation structural breaks in volatility modeling provides a better fit for the data. Our diagnostic tests also confirm that the model residuals are homoscedastic and exhibit zero or near zero autocorrelation. This summary affords two key messages: First, structural breaks in unconditional volatility of sector returns cannot be blithely ignored since they influence the conditional volatility of sector returns. Ignoring structural breaks leads to upward biased estimation of persistence of sector return volatility. This may cause erroneous forecasting of sector volatility, design of sectoral hedging strategies and incorrect pricing of sector-based derivative instruments. Second, structural break identification method does matter since different methods identify different number and locations of the breaks. The impacts the size of bias in estimated persistence of volatility. We further explore this issue in the next section.

Effects of number of breaks on persistence of volatility

We investigate further the relationship between the number of breaks and volatility persistence. According to Chen et al. (2006), the method used to measure volatility critically affects the results for any analysis of volatility or volatility persistence.

INSERT TABLE 5 AROUND HERE

Moreover, simulation studies by Výrost, Baumöhl and Lyócsa (2011) confirms that there is an inverse relationship between the number of breaks and persistence of volatility. Therefore, a model which overestimates the number of structural breaks will ultimately show lower persistence of volatility. We use a two prong approach: First, using results from table 4, we analyze the correlation between number of breaks and statistically significant persistence of volatility parameter, β. Second, we regress parameter β[10] on number of breaks in a simple regression analysis[11]. We assemble our results in table 5. The *IT* method had an average of 9.5 breaks and average persistence of 0.544. The correlation between number of breaks and persistence is -0.426. However, *k1 (k2)* records an average of 6 (4.4) breaks and an average persistence of 0.7278 (0.7753). The correlation between β and number of breaks, N_B for *k1* (*k2*) is -0.341 (-0.129). Our regression results show that a 1% increase in N_B, results in 3.32% decline in persistence of volatility. The N_B also explains 58% of variation in persistence of volatility. Overall, our results highlight the need to complement *IT* break-identification test with *k1* and *k2* tests to alleviate generation of overestimation of volatility persistence.

Dynamic correlation patterns among sectors

The US economic sectors are interconnected through mutual economic fundamentals variables such as fiscal and monetary policies and output growth. Therefore, it is imperative to investigate potential cross-sector information (volatility)[12] flow and dependence both of which could affect asset allocation and portfolio rebalancing decisions. We employ the corrected asymmetric dynamic conditional correlation (cADCC) model of Aielli (2013) which account for the

[10] We use only the statistically significant β coefficients, to mitigate potential adulteration of our results by insignificant β coefficient estimates.

[11] We use heteroskedasticity and autocorrelation consistent (HAC) estimation of Newey and West (1987) in regression estimation.

[12] Ross (1989) shows that volatility is a measure of information

direction, strength, time-variation and asymmetry of potential information spillovers through conditional correlations of conditional volatility of sector pairs. The building block of cADCC model is the dynamic conditional correlation (DCC) model of Engle (2002). We use the following equations to explain the model.

$$y_t = \mu + \varepsilon_t \tag{9}$$

$$\varepsilon_t = H_t^{0.5} z_t \tag{10}$$

$$H_t = D_t C_t D_t \tag{11}$$

$$D_t = diag\left(h_{11,t}^{0.5},....,h_{NN,t}^{0.5}\right) \tag{12}$$

$$C_t^{DCC} = diag[Q_t]^{-0.5} Q_t diag[Q_t]^{-0.5} \tag{13}$$

INSERT TABLE 6 AROUND HERE

In equations 9 through 13, y_t denotes returns of *k* sectors. μ is a vector of conditional expected returns $[\mu = E(y_t \mid \Phi_{t-1})]$ where Φ_{t-1} is information set including period *t-1* . ε_t is a vector of unexpected or mean adjusted sector returns at time *t*, z_t is a vector of independently and identically distributed (*iid*) errors where the mean, $E(z_t \mid \Phi_{t-1}) = 0$ and conditional second moment (variance), $Var(z_t \mid \Phi_{t-1}) = I_N$ where I_N is the identity matrix. H_t is the time-varying conditional covariance matrix of ε_t given Φ_{t-1} hence $[H_t]_{ij} = h_{it} h_{jt} \rho_{ij,t}$ where *i≠j, 1<i, j≤N.* $H_t^{0.5}$ is the Cholesky factorization of H_t . D_t is a diagonal matrix of conditional standard deviations, $h_{ii}^{0.5} \mid \Phi_t$. C_t represent the conditional correlation matrix while C_t^{DCC} is time-varying conditional correlation matrix. $diag[Q_t]$ is a matrix bearing similar diagonal as Q_t and have zero off-diagonal entries. Q_t is a matrix of quasi-correlations which evolve in GARCH-like recursion so that $Q_t = \overline{Q}(1-\alpha-\beta) + \alpha(\eta_{t-1}\eta'_{t-1}) + \beta Q_{t-1}$ where α (typical ARCH term) and β (typical GARCH

term) are non-negative scalars. The GARCH process is stationary if $\alpha + \beta < 1$. η_{t-1} is a vector of standardized residuals from a univariate GARCH model[13]. $\overline{Q} = T^{-1}\sum_{t=t}^{T}\hat{\eta}_\tau\hat{\eta}'_\tau$ is an identity matrix with the non-diagonal entries equal to unconditional sample correlation of standardized residuals. As long as Q_1 is positive definite, every successive Q_t will be positive definite and invertible since it is a weighted average of a series of positive definite matrices. The DCCs are computed as follows

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}}, i, j = 1,2,.....,n; i \neq j$$

Cappiello et a.l (2006a) permits incorporation of asymmetries in the correlation dynamics by adjusting the following equation

$$Q_t = \overline{Q}(1-\alpha-\beta) + \alpha(\eta_{t-1}\eta'_{t-1}) + \beta Q_{t-1} - \delta\overline{N} + \delta(n_{t-1}n_{t-1}{}' \quad (14)$$

Where $\overline{N} = T^{-1}\sum_{t=t}^{T}\hat{n}_t\hat{n}''_t$, $n_t = I[\varepsilon_t < 0] \circ \varepsilon_t$, $I[\bullet]$ is an indicator function taking the value of 1 if true otherwise 0. In (14), δ is the maximum eigen value equal to $[\overline{\mathrm{Q}}^{-0.5}\,\overline{N}\,\overline{\mathrm{Q}}^{-0.5}]$ which is asymmetry parameter. The positive definite of Q_t is ensured when $\alpha, \beta, \delta \geq 0$ and $\alpha + \beta + \delta < 1$

Aielli (2013) empirically shows that the moment estimator, Q, may be biased and inconsistent. He developed the corrected ADCC (cADCC) model by proposing the following process:

$$Q_t = \overline{Q} * (1-\alpha-\beta) + \alpha(\eta^*_{t-1}\eta^{*\prime}_{t-1}) + \beta Q_{t-1} - \delta\overline{N} + \delta(n_{t-1}n_{t-1}{}') \quad (15)$$

In (15), $\eta^*_t = diag\{Q_t\}^{0.5}$. This enables ε_t and $\overline{Q}*$ to be estimated consistently through a sample covariance matrix of η^*_t.

[13] To ensure consistent correlation estimate, we identify EGARCH using Bayesian information criterion (BIC) as the best univariate GARCH model that first the data best among standard GARCH, AVGARCH, NGARCH, EGARCH, GJR-GARCH, APARCH, TGARCH, and CSGARCH model specifications

Table 6 assembles cADCC coefficients, ρ, the impact of short term co-movement (ARCH) coefficient, α, the persistence (GARCH) coefficient, β and asymmetry coefficient, δ. The higher (lower) the ρ is, the stronger (weaker) the co-movement in pairs of sector volatility and the more linked (segmented) the sectors are. Segmented sectors offer potential portfolio risk diversification benefit. The strongest positive co-movement is between FIN and TEC (ρ=0.976) while both TEC-UTL and UTL-TEL pairs register insignificant dynamic corrections. The two sector-pairs afford the best opportunity for cross-sector hedging to diversify risk since in absence of correlation of returns, then, there are no overarching volatility or information spillovers between any of the two pairs of sectors, suggesting potential segmentation. Other sector pairs with high potential for diversification due to relatively low dynamic conditional correlation (below 0.5) are MAT-UTL, CDI-UTL, CSI-EGY, EGY-HCI, EGY-TEL, HCI-UTL and IND-UTL. The strong correlations are indicative of interdependence and potential information flow among the sectors. Most of the sector pairs have symmetric correlation with exception of CDI-EGY, CDI-FIN, CDI-IND, CDI-MAT, CDI-TEC, CDI-TEL, CSI-EGY, CSI-FIN, EGY-IND, FIN-IND, FIN-TEC, IND-MAT and TEC-TEL. These pairs have significant δ parameter estimate suggesting that impacts of positive and negative shocks to correlations are unequal over time. This evidence is important as correlation is a key input in risk diversification strategy.

We find no impact of short term or recent co-movement on correlation (insignificant α parameter estimate) in the following sectors pairs: CDI-IND, CDI-UTL, CDI-TEL, CSI-MAT, EGY-CDI, EGY-CSI, EGY-FIN, EGY-HCI, EGY-MAT, EGY-TEC and EGY-UTL. The energy sector is involved in seven of these pairs. Therefore, transitory co-movements do not affect co-movement between energy sector and seven other sectors. This evidence not only indicates the pervasive nature of energy on the overall economy (or other sectors) but also that any diversification effort using EGY sector should focus on impact of long term dynamic correlation. Generally, magnitude of the impact of short term co-movement on ADCC is generally low, ranging from 0% (insignificant α) and 8%.

All sector pair exhibit slow decay in correlations (or lack of it) as reflected in the high and significant β (persistence) parameter. Specifically, with MAT-UTL (HCI-IND) registers the strongest (weakest) positive dynamic correlation of 0.971 (0.789). Therefore, a shock to sector return is likely to influence expected dynamic correlation over many periods in future.

INSERT FIGURE 1 AROUND HERE

Figure 1 illustrates evolution of cADCC of selected[14] pairs of sectors. There is a notable heterogeneity of correlation patterns. Generally, the correlations remain stubbornly positive with major sporadic shifts to negative correlation zone. None of the pairs exhibit a stable correlation structure or pattern for a prolong period of time, suggesting that sector return volatility correlations incessantly change in response to returns shocks to each sector in the pair. It is clear correlation is time-varying hence using time-invariant point estimates may yield incorrect inference and decisions regarding risk management and portfolio rebalancing. Another interesting observation is the significant decline in positive correlations (with a few exceptions) and switch to negative correlation realm in some sector pairs, between 2000:01 and 2001:12. This period coincides with the Dot.Com burst in early 2000 and economic recession in year 2001.

We make three important conclusions with respect to cADCC. First, the zero or low dynamic correlation is partly caused by heterogeneous performance of sectors during over time,

[14] We present just a sample of graphs to save space. Essentially, there are 45 pairs of correlations. Other dynamic correlation graphs are available upon request.

perhaps over business cycles. This is consistent with the theory of sector rotation which purports that different sectors perform differently under different economic cycles. Therefore, investors ought to overweight best performing sector and underweight underperforming sectors in their portfolio over time to produce superior risk-adjusted portfolio returns relative to the overall market benchmark. Second, in majority of sector pairs, dynamic correlations exhibit slow decay or persistence hence it is possible to predict future correlations from past correlation patterns. This evidence infringes efficient market hypothesis.

V. Conclusion

These study sets out to investigate three main issues: First, how do structural breaks in unconditional volatility affect persistence of volatility of sector returns? Second, how does the structural breaks identification method (and hence the number of structural breaks) affect the persistence of volatility? Third, what is the nature of dynamic information flow across sectors? We use three different but nested methods to identify structural break points in unconditional volatility. We employ breaks-augmented EGARCH model to assess the effects of breaks on persistence of volatility. Lastly, we utilize the cADCC model to investigate transitory and persistent co-movements of pairs of sector return volatility. We uncover four interesting pieces of evidence: First, we not only find multiple structural breaks for each sector but heterogeneous magnitudes and break points among the sectors. Different break identification methods generate different number and location of the breaks with *k2* method (which account for most of the stylized facts of financial times series) yielding the least but strongest structural breaks in terms of statistical significance. Second, persistence of volatility is declining in the number of structural breaks. We can thus conclude that since different break methods generate different number and points of break, persistence of volatility is highly influenced by three factors videlicet location, scale and number of breaks. The three factors depend on the break identification method used. Therefore, the use of *IT* method alone leads to overestimation of volatility persistence. This has important implication for forecasting, asset pricing and valuation of contingent claims. The intrinsic value of financial assets is inversely related to expected persistence of volatility. Therefore, any upward or downward bias in estimating persistence of volatility will affect pricing of sector-based assets and derivative instruments. Third, consistent with past studies, we find that the presence of disruptive breaks make the unconditional volatility of all sectors to be time-varying. Therefore, econometric modeling that assumes constant mean returns and unconditional volatility may generate incorrect estimates, statistical inferences and more forecasting errors. Lastly, we find time-varying and highly persistent correlation structures in majority sector pairs, with only a few pairs registering insignificant correlation. This affects not only risk reduction strategies in sector index investing, but also the potential for cross-sector hedging and sharing of mutual information in making optimal portfolio allocation decisions. Future studies may investigate, in addition to business cycles, the key drivers of dynamic correlation patterns across sectors.

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Table 1: Data characteristics and models specification tests

Sector	Mean	S. D	C.V	Skew	Kurtosis	RJB	N	ARCH(13)	LB(13)	$LB^2(13)$
CDI	0.177	2.872	16.234	-0.666	8.092	***1741.45	1049	***17.018	***35.35	***379.13
CSI	0.205	1.855	9.034	-0.716	6.813	***879.49	1049	***7.749	14.86	***142.71
EGY	0.232	3.155	13.596	-0.653	6.284	***563.44	1049	***18.424	15.49	***446.16
FIN	0.157	3.363	21.456	-0.646	11.561	***7592.63	1049	***16.822	***46.72	***526.97
HCI	0.228	2.298	10.097	-0.467	6.076	***593.28	1049	***5.561	**22.95	***97.24
IND	0.189	2.750	14.526	-0.749	7.136	***1301.93	1049	***11.850	***36.03	***277.69
MAT	0.159	3.094	19.485	-0.574	6.156	***651.68	1049	***19.413	***35.01	***481.91
TEC	0.188	3.835	20.373	-0.528	5.654	***468.74	1049	***14.162	***39.31	***482.06
UTL	0.164	2.318	14.122	-0.909	10.089	***4172.68	1049	***12.543	15.14	***260.31
TEL	0.031	3.240	103.595	-0.510	7.672	***1256.35	814	***9.049	**23.13	***253.27

Notes: S.D is the standard deviation. C.V is the coefficient of variation equal to S.D/mean. RJB is the robust Jacque-Bera test of Gel and Gastwirth (2008). N is the number of observations (weeks). ARCH (13) is the autoregressive conditional heteroskedasticity test of Engle (1982) at 13 lag orders (weeks). LB (13) and LB^2 (13) are the Ljung-Box serial correlation test of Ljung and Box (1978) of residuals and squared residuals. *, ** and *** show statistical significance at 10%, 5% and 1% significance levels respectively.

Table 2: Maximum likelihood estimation of EGARCH without structural breaks

Sector	λ	α	γ	β	HL	ARCH(16)	LB(16)	$LB^2(16)$
CDI	***-0.061	***0.153	***-0.137	***0.966	19.802	1.192	14.897	19.114
CSI	***-0.089	***0.221	***-0.146	***0.920	8.288	1.307	17.631	21.072
EGY	***1.307	***0.163	***-0.113	***0.951	13.709	0.895	11.817	14.596
FIN	***-0.095	***0.193	***-0.115	***0.971	23.339	0.832	18.924	13.573
HCI	-0.001	***0.234	***-0.168	***0.877	5.259	0.644	20.382	9.6899
IND	-0.019	***0.111	***-0.147	***0.959	16.492	0.994	15.046	16.141
MAT	-0.039	***0.117	***-0.106	***0.973	25.668	1.357	18.04	21.19
TEC	***-0.095	***0.181	***-0.080	***0.979	32.517	1.23	22.424	19.755
UTL	***-0.100	***0.228	***-0.097	***0.945	12.218	0.929	22.329	13.82
TEL	*-0.055	***0.136	***-0.129	***0.971	23.187	0.337	19.353	5.439

Notes: Notes: ARCH (16) is the Engle (1982) test with the null of constant variance (homoscedasticity) of residuals. HL is half-life for EGARCH model which is computed as $–\ln(2)/\ln(\beta)$. LB(16) is the Ljung and Box (1978) test of serial autocorrelation of residuals. ***, ** and * shows statistical significance at 1%, 5% and 10% significance levels respectively

Table 3: Number of structural Break and break points or dates using IT, Kappa-1 and Kappa-2 methods

Sector	N_{BIT}	T_{BIT}		N_{BK1}	T_{BK1}		N_{BK2}	T_{BK2}	
CDI	11	12/6/1995	7/15/1998	7	12/6/1995	7/15/1998	7	12/6/1995	7/15/1998
		3/12/2003	5/19/2004		5/19/2004	7/11/2007		5/19/2004	7/11/2007
		7/11/2007	9/24/2008		6/18/2008	7/15/2009		6/18/2008	7/15/2009
		11/19/2008	3/11/2009		12/14/2011			12/14/2011	
		8/18/2010	7/20/2011						
		12/14/2011							
CSI	9	11/22/1995	3/12/2003	6	11/22/1995	3/12/2003	6	11/22/1995	3/12/2003
		4/27/2005	7/18/2007		4/27/2005	7/18/2007		4/27/2005	7/18/2007
		9/24/2008	10/8/2008		9/3/2008	7/8/2009		9/3/2008	7/8/2009
		3/18/2009	7/27/2011						
		8/10/2011							
EGY	8	3/12/1997	11/13/2002	8	11/22/1995	3/12/1997	5	3/12/1997	11/13/2002
		9/22/2004	6/25/2008		11/13/2002	9/22/2004		9/22/2004	1/2/2008
		11/26/2008	7/8/2009		1/2/2008	7/8/2009		7/8/2009	
		7/20/2011	12/14/2011		7/20/2011	12/14/2011			
		10/11/1995	7/15/1998						
FIN	9	3/12/2003	7/11/2007	7	10/11/1995	7/15/1998	7	10/11/1995	7/15/1998
		9/3/2008	5/6/2009		3/12/2003	7/11/2007		3/12/2003	7/11/2007
		8/25/2010	7/27/2011		9/3/2008	5/6/2009		9/3/2008	5/6/2009
		12/14/2011			12/14/2011			12/14/2011	
HCI	10	11/15/1995	7/15/1998	3	11/15/1995	3/31/2004	2	11/15/1995	11/13/2002
		11/13/2002	3/31/2004		10/24/2007				
		10/24/2007	3/5/2008						
		9/24/2008	3/11/2009						
		7/13/2011	8/10/2011						
IND	10	7/15/1998	1/6/1999						
		2/28/2001	3/12/2003	8	7/15/1998	3/12/2003	5	7/15/1998	3/12/2003
		7/4/2007	6/18/2008		7/4/2007	8/27/2008		7/4/2007	8/27/2008
		3/11/2009	8/25/2010		3/11/2009	8/25/2010		9/9/2009	
		7/13/2011	12/14/2011		7/13/2011	12/14/2011			
TEC	9	8/19/1998	3/12/2003						
		11/10/2004	7/18/2007	5	8/19/1998	3/12/2003	2	8/19/1998	3/12/2003
		8/20/2008	11/19/2008		11/10/2004	10/17/2007			
		7/15/2009	7/27/2011		12/7/2011				
		12/7/2011							
MAT	10	1/24/1996	10/15/1997	6	8/19/1998	3/12/2003	4	8/19/1998	3/12/2003
		12/1/1999	3/12/2003		7/4/2007	8/25/2010		7/4/2007	1/4/2012
		7/4/2007	9/17/2008		7/20/2011	1/4/2012			
		1/7/2009	8/25/2010						

		7/20/2011	1/4/2012					
		11/5/1997	8/23/2000					
UTL	9	6/26/2002	2/12/2003	4	11/5/1997	8/23/2000	4	11/5/1997	8/23/2000
		8/20/2008	3/11/2009		6/26/2002	2/12/2003		6/26/2002	2/12/2003
		11/9/2011	12/14/2011						
		10/3/2012							
TEL	9	3/6/1996	10/14/1998	6	3/6/1996	10/14/1998	2	3/6/1996	10/14/1998
		11/3/1999	4/23/2003		11/3/1999	1/29/2003			
		3/3/2004	5/19/2004		3/3/2004	9/8/2004			
		9/8/2004	5/9/2007						
		6/13/2007							
USA	11	12/6/1995	7/15/1998	7	12/6/1995	7/15/1998	7	12/6/1995	7/15/1998
		3/12/2003	5/19/2004		5/19/2004	7/11/2007		5/19/2004	7/11/2007
		7/11/2007	9/24/2008		6/18/2008	7/15/2009		6/18/2008	7/15/2009
		11/19/2008	3/11/2009		12/14/2011			12/14/2011	
		8/18/2010	7/20/2011						
		12/14/2011							

Notes: N_{BIT}, N_{BK1} and N_{BK2} are number of structural breaks using IT, Kappa-1 and Kappa-2 methods respectively. T_{BIT}, T_{BK1} and T_{BK2} are the structural break points or dates identified by IT, Kappa-1 and Kappa-2 methods respectively.

Table 4: Maximum Likelihood Estimation with Structural breaks

SECTOR		λ	α	γ	β	ARCH(16)	LB(16)	F-Dum	LR
CDI	IT	0.303	-0.062	***-0.248	***0.395	1.108	18.505	***3.569	***87.928
	K^2	0.182	-0.027	***-0.284	***0.718	1.286	18.571	***3.633	***76.488
CSI	IT	0.122	*0.098	***-0.202	***0.669	0.869	20.555	***3.049	***76.270
	K^2	0.131	*0.096	***-0.235	***0.703	1.125	19.513	***4.097	***61.986
EGY	IT	0.532	**0.143	***-0.148	***0.506	0.925	17.873	**2.304	***65.690
	K1	0.330	**0.158	***-0.156	***0.439	1.015	16.386	**2.341	***57.258
	K2	0.073	***0.130	***-0.139	***0.863	1.314	14.942	*1.961	***22.142
FIN	IT	0.860	0.094	-0.058	0.331	*1.583	23.315	***3.615	***73.114
	K^2	0.198	0.070	***-0.177	***0.743	**1.743	21.475	**2.355	***57.644
HCI	IT	0.791	*0.128	***-0.163	0.143	0.953	**28.779	***5.433	***82.436
	K1	0.228	0.098	***-0.265	***0.733	0.807	20.5	***6.278	***46.524
	K2	0.133	***0.181	***-0.228	***0.755	0.768	19.043	***7.037	***29.992
IND	IT	0.375	0.076	***-0.186	***0.606	0.811	18.172	1.085	***58.696
	K1	0.345	0.083	***-0.201	***0.634	0.897	19.463	1.404	***59.316
	K2	0.226	*0.104	***-0.227	***0.739	1.241	16.138	**2.239	***39.888
MAT	IT	3.622	-0.067	-0.059	0.445	*1.593	***29.776	***2.918	***317.132
	K1	0.365	0.057	***-0.165	***0.840	1.262	*24.717	***3.194	***333.286
	K2	0.078	***0.119	***-0.119	***0.936	*1.591	22.579	***7.681	***359.878
TEC	IT	1.395	**0.186	-0.072	0.181	1.149	20.003	***3.813	***468.69
	K1	0.367	***0.160	***-0.137	***0.614	1.067	21.562	**2.112	***419.678
	K2	0.077	**0.103	***-0.125	***0.882	1.029	23.153	1.881	***409.766
UTL	IT	0.232	**0.189	**-0.109	0.273	0.580	19.628	1.137	***66.512
	K^2	-0.06	***0.242	***-0.140	***0.798	0.994	23.539	**2.464	***23.546
TEL	IT	2.008	0.079	***-0.155	0.123	0.345	16.111	1.582	***59.978
	K1	0.037	***0.102	***-0.142	***0.957	0.687	19.878	1.545	***9.384
	K2	0.959	***0.128	***-0.194	***0.616	0.687	16.163	**3.237	***36.758

Notes: IT is the modified Inclan and Tiao (1994) ICSS method. K^2 means that K1 and K2 methods yield the same of number and points of breaks hence no need for separate K1 and K2. LR is the likelihood ratios computed as $-2[L(\Phi_0)-L(\Phi_b)]$ where $L(\Phi_b)$ and $L(\Phi_0)$ are the log-likelihoods for EGARCH models with and without structural breaks in variance. F (DUM) is the F- statistic for the joint test of joint significance of the dummy variables (DUM). ARCH (16) is Engle's (1982) ARCH-LM test up to 16 lags. ***, ** and * shows statistical significance at 1%, 5% and 10% significance levels respectively

Table 5: Relationship between number of breaks, N_B and persistence, β

Method->	IT		K1		K2	
Sector	N_B	β	N_B	β	N_B	β
CDI	11	0.395	7	0.718	7	0.718
CSI	9	0.669	6	0.703	6	0.703
EGY	8	0.506	8	0.539	5	0.863
FIN	9	0.33	7	0.743	7	0.743
HCI	10	0.142	3	0.732	2	0.755
IDU	10	0.606	8	0.634	5	0.739
TEC	9	0.181	5	0.614	2	0.882
MAT	10	0.445	6	0.84	4	0.936
UTI	9	0.273	4	0.798	4	0.798
TEL	9	0.123	6	0.957	2	0.616
Average	9.5[a]	0.544[a]	6	0.7278	4.4	0.7753
Correlation		-0.426[a]		-0.341		-0.129

Regression Analysis

Dependent variable: β	*Coefficients*	*Std Error*	*t Stat*	*P-value*	R^2
Constant	0.9092	0.0637	***14.280	0.0000	0.579
N_B	-0.0332	0.0099	-3.329		0.0030

Notes: N_B is the number of structural breaks under each method (IT, K1 and K2) while β is the persistence of volatility estimator under each method. The letter a means that the average N_B and correlation for IT method are based on statistically significant β coefficient (0.395, 0.669, 0.506 and 0.606). ***, ** and * shows statistical significance at 1%, 5% and 10% significance levels respectively

Table 6: cADCC, Short term volatility co-movement and persistence of correlation

Sector		CSI	EGY	FIN	HCI	IND	MAT	TEC	UTL	TEL
CDI	**ρ**	***0.685	***0.606	***0.951	***0.689	***0.875	***0.765	***0.769	***0.454	***0.726
	α	***0.046	***0.029	***0.051	***0.080	0.033	**0.079	**0.051	0.057	0.015
	β	***0.940	***0.943	***0.945	***0.813	***0.838	***0.838	***0.927	***0.915	***0.901
	δ	0.001	***0.045	**-0.028	0.037	*0.093	*0.067	**0.036	-0.007	**0.066
CSI	**ρ**		***0.456	***0.701	***0.746	***0.627	***0.550	***0.626	***0.520	***0.579
	α		**0.043	***0.032	**0.039	***0.064	0.028	***0.059	*0.029	***0.049
	β		***0.909	***0.953	***0.943	***0.894	***0.873	***0.922	***0.963	***0.928
	δ		***0.044	**-0.023	-0.002	0.039	0.071	0.001	0.001	0.013
EGY	**ρ**			***0.563	***0.422	***0.613	***0.668	***0.527	***0.513	***0.496
	α			0.027	0.041	**0.034	0.021	0.017	0.005	***0.045
	β			***0.947	***0.854	***0.934	***0.959	***0.959	***0.964	***0.917
	δ			0.042	0.104	**0.042	0.031	0.039	0.030	0.036
FIN	**ρ**				***0.696	***0.976	***0.720	***0.530	***0.519	***0.689
	α				***0.062	***0.054	**0.040	***0.045	0.032	0.025
	β				***0.840	***0.943	***0.950	***0.955	***0.882	***0.920
	δ				0.032	***-0.027	0.015	***0.000	0.043	0.039
HCI	**ρ**					***0.688	***0.580	***0.695	***0.488	***0.612
	α					***0.079	***0.068	***0.058	*0.030	**0.035
	β					***0.789	***0.877	***0.913	***0.953	***0.936
	δ					0.077	0.036	-0.013	0.009	-0.001
IND	**ρ**						***0.831	***0.765	***0.497	***0.702
	α						**0.051	0.031	0.017	***0.055
	β						***0.894	***0.959	***0.960	***0.898
	δ						*0.060	0.013	0.014	0.024
MAT	**ρ**							***0.689	***0.456	***0.621
	α							**0.024	0.004	***0.049
	β							***0.958	***0.971	***0.910
	δ							0.029	0.027	0.034
TEC	**ρ**								0.088	***0.717
	α								***0.033	0.004
	β								***0.965	***0.910
	δ								0.000	***0.066
UTL	**ρ**									0.030
	α									**0.041
	β									***0.955
	δ									0.031

Notes: *ρ, α, β and γ* represent corrected asymmetric dynamic conditional correlation (cADCC), short term co-movement (ARCH), GARCH and asymmetry of correlation respectively. ***, ** and * shows statistical significance at 1%, 5% and 10% significance levels respectively.

Figure 1: Sample Corrected ADCC between stock returns volatility of two sectors