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ORIGINAL RESEARCH

Volatility spillover among sector equity returns under structural breaks

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Abstract
Recent evidence suggests that ignoring structural breaks in volatility in financial asset returns can result in overestimation of volatility spillover among markets. This paper examines volatility spillover among major US equity sectors (i.e. Financial, Technology, Energy, Health, Consumer and Industrial) with bivariate GARCH models utilizing daily data from April 2006 to March 2021 after adjusting for volatility breaks. I find significantly less volatility spillover between sector returns after adjusting for detected volatility breaks into a bivariate GARCH model. I also show that after adding volatility breaks into a model the estimated hedge ratios change significantly and show considerably less variability over time, which can result in substantial savings in portfolio rebalancing costs.

Keywords Volatility spillover · Equity volatility · Structural breaks · GARCH

JEL Classification G1

1 Introduction

Sector index investing has become very prevalent over the last 2 decades due to the popularity of exchange traded funds. Returns on different equity sectors are generally strongly positively correlated over the long run but there can be substantial differences in the short run. For example, last year (2020), technology sector index increased by 40% while financial sector index decreased by 5%. In the first quarter of this year (2021), we see an opposite pattern as technology sector index has increased by only 2% while financial sector index has gained by a sizable amount of 15%. Not surprisingly, daily fluctuations in sector indexes are closely monitored by investors and policy makers. Therefore, there has been a substantial research which has explored the empirical and theoretical relationship among major equity sector returns.

The earlier line of literature had studied the empirical relationship among equity sectors in the level form. Notable studies include Ewing (2002) who used a vector auto-regression approach to examine the relationship among five major equity sectors. Using monthly data

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from S&P stock sector indexes from January 1988 to July 1997; he documents significant impact of shocks from one sector to other sector returns. Ewing et al. (2003) analyze the effects of unanticipated macroeconomic news on five major S&P equity sector indexes using data after the 1987 crash period. Using generalized impulse response analysis, they show that equity sector returns are significantly more impacted by macroeconomic shocks relative to some predictable events. Meric et al. (2008) study the relationship among sector indexes in the US, UK, German, French, and Japanese stock markets during a bull and bear markets using Granger causality tests. They report that during a bull market investors are better off if they invest in the same sector in a different country rather than investing in different sectors within the same country. In contrast, the sectors of different countries are highly correlated during a bear market, which restricts diversification benefits across countries.

However, there are many credible reasons which suggest that the volatility from one equity sector may spillover to other sectors. Three lines of thoughts have emerged in the literature which can explain these volatility spillover effects. First, volatility spillovers may result from hedging across markets carried out by investors due to changes in common information across sectors which instantaneously changes expectations. Fleming et al. (1998) provide a model that shows how hedging combined with sharing of common information across markets will lead to volatility spillover across financial markets over time. Second, mean and volatility spillover could be due to financial contagion, where a shock to one financial market may cause a change in asset prices in other financial markets. Kodres and Pritsker (2002) give a multiple-asset rational expectations model to explain contagion in financial markets. They show that investors transmit shocks among financial markets by modifying their portfolio exposure to different macroeconomic risks. They argue that the amount of financial contagion is primarily determined by how sensitive the market is to the underlying shared macroeconomic risk factors and the extent of information asymmetry among financial markets. Third, Ross (1989) proposed a model where volatility in financial asset returns depends upon the rate of information flow. Since one would expect different rates of information flow across sectors and also the time used in processing such information may vary across sectors, thus we should expect different volatility patterns across sectors over time.

Although there has been an explosion in the literature on the studies of volatility spillovers between financial markets, it is interesting to note that there have been relatively few studies that have examined volatility spillover among equity sector returns. The first study on this topic was conducted by Hassan and Malik (2007) who used a multivariate GARCH model to model volatility among major US equity sector indexes. They show a significant transmission of volatility among sectors and document the corresponding economic implications.[1] Recent studies include, Nguyen et al. (2020), who examine the volatility spillover across industries and its dependence on the inter-industry business linkages. They document significant cross-industry volatility spillovers, which they attribute to the strength of the trade relationship between industries. Mensi et al. (2021) examine the dynamic asymmetric volatility connectedness among ten US stock sectors. They provide evidence of time-varying spillovers among US stock sectors and they show that these spillovers gain intensity during major economic, energy and geopolitical events.

[1] In a related study, Malik and Ewing (2009) show substantial transmission of shocks and volatility between oil prices and US equity sector returns.

There are many methods to estimate time-varying volatility in financial asset prices. One such popular method is a GARCH model, which is built on an assumption that volatility is produced from a stable GARCH process. This assumption is seriously questioned as widespread empirical evidence suggests that there are structural breaks (shifts) in the unconditional variance of stock returns (Starica and Granger 2005; Hood and Malik 2018). Starica and Granger (2005) underscore the need to adjust for structural breaks in volatility of financial asset prices. Ewing and Malik (2005) were the first to account for such structural breaks to correctly estimate the volatility spillover across markets within a bivariate GARCH model. They provide empirical evidence which shows that volatility spillover is reduced between small cap and large cap US stock returns when breaks in volatility are added in the bivariate GARCH model. A later study by Marcelo et al. (2008) further documents that volatility spillover effects are substantially reduced when volatility breaks are adjusted for in the small and large cap Spanish equities. Similarly, Huang (2012) shows that there is bidirectional volatility spillover between stock returns of the UK and the US but this spillover effect is disappeared after volatility breaks in the bivariate GARCH model are accounted for. Recently, Caporin and Malik (2020) document using comprehensive Monte Carlo simulations that induced structural breaks in volatility across two independent return series will display significant (spurious) volatility spillover effects when estimated with popularly used bivariate GARCH models. Given this widespread evidence, this paper examines the volatility spillover between equity sector returns adjusting for structural breaks in volatility using the framework originally proposed by Ewing and Malik (2005). To the best of my knowledge, this is the first paper which studies the volatility spillover between US sector equity returns after accounting for structural breaks in volatility.

Specifically, this paper studies the volatility spillover between six major US equity sector stock returns (i.e. Financial, Technology, Energy, Health, Consumer and Industrial) using daily data from April 2006 to March 2021. First, I document significant *bidirectional* volatility transmission between sectors in all six bivariate GARCH models (i.e. financial-technology, financial-energy, technology-energy, health-industrial, health-consumer and industrial-consumer) if breaks are ignored, which is consistent with Hassan and Malik (2007). Then using modified iterative cumulative sum of squares (ICSS) algorithm proposed by Inclan and Tiao (1994), I show significant structural breaks in volatility in all six sector returns, some corresponding to major news event like the COVID-19. After incorporating these volatility breaks into the GARCH model, I find significant reduction in volatility spillover and only find *unidirectional* volatility spillover (i.e. only one sector transmits volatility to the other sector but not vice versa). Specifically, I find that after incorporating breaks in the model, volatility from financial sector no longer spillover to technology sector, volatility from energy sector no longer spillover to financial sector, volatility from energy sector no longer spillover to technology sector, volatility from health sector no longer spillover to industrial sector, volatility from consumer sector no longer spillover to health sector, and volatility from consumer sector no longer spillover to health sector These findings could be due to hedging by investors across these sectors and show an estimation bias in the standard bivariate GARCH models as they have a tendency to overestimate the volatility spillovers when volatility breaks are not accounted for as documented by Caporin and Malik (2020). I also report that when structural breaks are added into a model, estimated hedge ratios change significantly and show considerably less variability. This less variability in hedge ratios can result in substantial savings for investors as they no longer need to frequently rebalance their portfolios. I also extend the work of Caporin and Malik (2020) by conducting and reporting my own set of Monte Carlo simulations with parameter settings which are more suitable to the data used in this paper.

These results are important for forecasting volatility in sector returns and will improve our understanding of the broader equity markets. Furthermore, since many financial assets are traded in the market based on these sector equity indexes, it is imperative for investors to understand how volatility is transmitted across these sectors so they can make correct adjustments to their portfolios and correctly price financial assets. My findings are also useful for policy makers as accurately estimating volatility spillovers are very important to devise policies to curtail a spread of risk across sectors especially during a period of market turmoil.

2 Empirical methodology

In this section, I describe the method I use to find significant structural breaks in volatility of sector returns, followed by describing the bivariate GARCH models used in the study. Then, I provide a description on how volatility breaks are incorporated into the bivariate GARCH model to correctly estimate the volatility spillover between sector returns.

2.1 Detecting structural breaks in volatility

Hillebrand (2005) conclusively shows that if a GARCH process undergoes a break then this will result in a break in the unconditional variance of the return series. Inclan and Tiao (1994) give cumulative sums of squares (*IT*) statistic which can be used to test the null hypothesis of a constant unconditional variance against the alternative hypothesis that there is a break in the unconditional variance. Their original test was designed for a return generating process which is independently distributed.

However, Sanso et al. (2004) demonstrate that the statistic proposed by Inclan and Tiao (1994) when applied to a series with dependent process (like GARCH) will result in substantial size distortions. They propose a non-parametric correction to the original *IT* statistic so it can be applied to a dependent process like GARCH. Inclan and Tiao (1994) also propose an iterated cumulative sums of squares (ICSS) algorithm which can be used on the *IT* statistic for detecting unlimited number of breaks in the unconditional variance of a return series. This algorithm when used on the modified *IT* statistic (with non-parametric correction) circumvents the issues that arise when the original *IT* statistic is used on a dependent process. In this study, I use the modified ICSS algorithm (i.e. using original ICSS algorithm to the modified *IT* statistic) as proposed by Sanso et al. (2004) to find breaks in the unconditional variance of sector index returns. Sanso et al. (2004) show through detailed theoretical proofs, Monte Carlo simulations and real-world data that their proposed method (which I use in this paper) correctly identifies structural breaks. I employ the standard 5% level of significance for testing multiple breaks in the unconditional variance of each sector index return series.[2]

2.2 Bivariate GARCH model

The mean equation estimated for each sector return series is given as

[2] Rapach and Strauss (2008) provide a comprehensive explanation of the methodology used in this paper as they use this method as well to detect significant structural breaks in volatility of exchange rates.

$$R_t = \mu + \rho R_{t-1} + \varepsilon_t \tag{1}$$

where R_t represents the individual sector index return and ε_t is assumed to have a normal distribution with a mean of zero. Following Aggarwal et al. (1999), I use an AR(1) process in the above equation as Q-statistic showed significant autocorrelation in each of the sector index returns. I applied the modified ICSS algorithm on the residuals of the individual sector returns to detect structural breaks in variance.

With respect to the bivariate GARCH (1, 1) model, I estimate the benchmark BEKK parameterization proposed by Engle and Kroner (1995) which is given as

$$H_{t+1} = C'C + B'H_tB + A'\varepsilon_t\varepsilon_t'A \tag{2}$$

For my bivariate case, C is a 2×2 lower triangular matrix and B is a 2×2 matrix which indicates how current volatility is impacted by the volatility in the last time period. A is a 2×2 matrix which shows how current volatility is impacted by the squared errors in the last time period. For my bivariate case, the total estimated number of parameters would be eleven.

The above volatility equation can be expanded as

$$h_{11,t+1} = c_{11}^2 + b_{11}^2 h_{11,t} + 2b_{11}b_{21}h_{12,t} + b_{21}^2 h_{22,t} + a_{11}^2\varepsilon_{1,t}^2 + 2a_{11}a_{21}\varepsilon_{1,t}\varepsilon_{2,t} + a_{21}^2\varepsilon_{2,t}^2 \tag{3}$$

$$h_{22,t+1} = c_{12}^2 + c_{22}^2 + b_{12}^2 h_{11,t} + 2b_{12}b_{22}h_{12,t} + b_{22}^2 h_{22,t} + a_{12}^2\varepsilon_{1,t}^2 + 2a_{12}a_{22}\varepsilon_{1,t}\varepsilon_{2,t} + a_{22}^2\varepsilon_{2,t}^2 \tag{4}$$

Equations (3) and (4) captures how shocks and volatility spillover exist across the two sector return series over a period of time.[3] I use the quasi-maximum likelihood estimation using robust standard errors as proposed by Bollerslev and Wooldridge (1992).

2.3 Bivariate GARCH model with structural breaks in variance

Following Ewing and Malik (2005), I augment the bivariate GARCH model with dummy variables to account for breaks in volatility as

$$\mathrm{H}_{t+1} = \mathrm{C}'\mathrm{C} + \mathrm{B}'\mathrm{H}_t\mathrm{B} + \mathrm{A}'\varepsilon_t\varepsilon_t'\mathrm{A} + \sum_{i=1}^{n} \mathrm{D}_i'\,\mathrm{X}_i'\,\mathrm{X}_i\mathrm{D}_i. \tag{5}$$

Equation (5) differs from Eq. (2) because of the extra term D_i which is a 2×2 square diagonal parameter matrix and X_i is a 1×2 row vector of dummies where n is the number of volatility breaks identified by the modified ICSS algorithm. The first (second) element in X_i row vector denotes the dummy for the first (second) series. If a volatility break is identified at time "t" in a series, then the corresponding element in X_i will take a value of 1 from time "t" afterwards and a value of 0 before time "t".

[3] It is pertinent to note that the coefficient terms in Eqs. (3) and (4) depend on the parameters from Eq. (2) in a non-linear fashion. Thus, I follow Ewing and Malik (2005) to compute the standard errors for these coefficient terms by using a first-order Taylor expansion around the mean.

Table 1 Descriptive statistics

	Financial	Technology	Energy	Health	Consumer	Industrial
Mean	0.000068	0.000507	− 0.000018	0.000344	0.000279	0.000262
Median	0.000541	0.001127	0.000384	0.000758	0.000499	0.000785
Minimum	− 0.18639	− 0.14983	− 0.22417	− 0.10528	− 0.09690	− 0.12155
Maximum	0.172013	0.11461	0.169604	0.11713	0.08835	0.12000
SD	0.02101	0.01455	0.01918	0.01130	0.00949	0.01427
Skewness	− 0.22762	− 0.32471	− 0.68899	− 0.23050	− 0.17040	− 0.52261
Kurtosis	18.4579	13.0000	18.8934	13.9752	17.3015	12.0832
Jarque–Bera	37,617.06	15,795.59	40,030.75	18,980.13	32,189.67	13,149.17

Sample includes daily sector index returns from April 1, 2006 to March 31, 2021. Total number of observations is 3775. Jarque–Bera statistic detects if a series deviates from a normal distribution and in all three sector index returns above I reject the null hypothesis of normality at 1% level. The correlation between Financial-Technology sector returns was 0.72, the correlation between Financial-Energy sector returns was − 0.08 and correlation between Technology-Energy sector returns was − 0.07. The correlation between Health-Industrial sector returns was 0.77, the correlation between Health-Consumer sector returns was − 0.13 and correlation between Industrial-Consumer sector returns was − 0.12

3 Data

I use daily closing prices from the sector equity data from April 1, 2006 to March 31, 2021.[4] I use the *S&P Dow Jones* sector indexes and the data was obtained from *Bloomberg*. In my analysis, I specifically study the following six major sector indexes: financials, (information) technology, energy, health, consumer (staples) and industrial.[5] These *S&P Dow Jones* sector indexes are widely used by investors and policy makers to track movements of these sectors. Additionally, these sector indexes are publicly reported to provide a measure for individual sector performance. These indexes represent a large number of major firms and industries within the US. The financial sector index comprises of big corporations dealing with banks, asset management, insurance companies, consumer finance, mortgage companies, etc. The (information) technology sector index is made up of companies which deal in telecommunications, software, semiconductors, computer (hardware and software), internet, etc. The energy sector index comprises of major US companies who are engaged in the energy sector like oil refining, oil exploration, etc. Health index includes health-care providers and services, companies that manufacture and distribute health-care equipment and supplies, and health-care technology companies including pharmaceutical and biotechnology companies. Consumer staples index covers businesses that are less sensitive to economic cycles, including manufacturers and distributors of food, beverages, and producers of non-durable household goods and personal products including food and drug retailers. Industrial index includes manufacturers and distributors of capital goods such as building products, electrical equipment and machinery, and aerospace and defense including

[4] I have used 15 years of most recent daily data to be consistent with earlier relevant studies mentioned in this paper.

[5] I selected these six sectors based on the popularity in the news media and these are the ones most studied based on the cited literature including Hassan and Malik (2007).

providers of commercial services such as construction and engineering, printing, environmental services, human resource services, research and consulting services, and transportation services. In line with previous research, I use log returns as all series in level form possessed a unit root.

Table 1 displays descriptive statistics for each of the sector return series. As can be seen from Table 1, all six of the sector returns series shows excessive kurtosis which shows that a GARCH model would be the appropriate choice to estimate volatility. All six sector returns series show negative skewness. As expected, Jarque–Bera statistic for all six sector returns rejects normality hypothesis at the 1% significance level. The correlation between Financial-Technology sector returns was 0.72, the correlation between Financial-Energy sector returns was − 0.08 and correlation between Technology-Energy sector returns was − 0.07. The correlation between Health-Industrial sector returns was 0.77, the correlation between Health-Consumer sector returns was − 0.13 and correlation between Industrial-Consumer sector returns was − 0.12.

4 Empirical results

The modified ICSS algorithm identified 9 structural breaks in the financial sector returns, 5 breaks in the technology sector returns, 11 breaks in the energy sector returns, 2 structural breaks in the health sector returns, 5 breaks in the consumer sector returns and 12 breaks in the industrial sector returns. These detected breaks are presented in Table 2 and displayed in Figs. 1, 2, 3, 4, 5 and 6. Two things are clearly noticeable from these detected breaks. First, all sectors (except health sector) experience an upward shift of more than double magnitude with the advent of financial crisis of 2007–2008. Second, around Feb 20, 2020 all sectors (except consumer) experience more than doubling of volatility which coincides with the market uncertainty induced by the COVID-19. Although these findings are not surprising but Caporin and Malik (2020) document if markets experiencing a common volatility break are more likely to show a significant spurious volatility spillover effect if these breaks are not accounting for.

Next, I estimate the volatility spillover between sector index returns using a bivariate GARCH model without adjusting for volatility breaks. Panel A of Table 3 presents the results for the financial and technology sector. I find that both financial sector and technology sector volatility is significantly impacted by its own ‘news’ and volatility (see the coefficients of h_{11} and ε_1^2 in the first equation and coefficients of h_{22} and ε_2^2 in the second equation as statistically significant at the 5% significance level). The results also show a significant volatility spillover from each sector to the other sector. This result is consistent with previous research findings of Hassan and Malik (2007) as they show significant volatility spillover across sectors. A clear implication of these results would be that investors in either sector need to keep a close eye on the other sector movement as bidirectional volatility (risk) spillover exists.

Next, I estimate the bivariate GARCH model after adjusting for identified volatility breaks and the results are given in Panel B of Table 3. Like earlier results, sectors returns are impacted by its own ‘news’ and volatility from prior time period. However, it is important to note that there is now only a unidirectional volatility spillover. In other words, volatility in technology sector significantly affects volatility of financial sector but financial sector has an insignificant impact on volatility of technology sector. This result is consistent with Caporin and Malik (2020), who argue that if volatility breaks are present and

Table 2 Detected volatility breaks

Series	Break points	Time period	SD
Financial	9	April 1, 2006–July 27, 2006	0.009262
		July 28, 2006–Feb 21, 2007	0.005357
		Feb 22, 2007–March 20, 2007	0.015124
		March 21, 2007–July 22, 2007	0.008682
		July 23, 2007–July 2, 2008	0.022503
		July 3, 2008–May 17, 2009	0.061743
		May 18, 2009–Aug 1, 2012	0.018331
		Aug 2, 2012–Aug 18, 2015	0.008674
		Aug 19, 2015–Feb 20, 2020	0.011001
		Feb 21, 2020–March 31, 2021	0.028214
Technology	5	April 1, 2006–Oct 17, 2007	0.009767
		Oct 18, 2007–Sept 11, 2008	0.015966
		Sept 12, 2008–Dec 7, 2008	0.044282
		Dec 8, 2008–April 20, 2009	0.025676
		April 21, 2009–Feb 20, 2020	0.011312
		Feb 21, 2020–March 31, 2021	0.025186
Energy	11	April 1, 2006–Oct 17, 2007	0.013941
		Oct 18, 2007–Sept 4, 2008	0.019550
		Sept 5, 2008–Nov 27, 2008	0.066360
		Nov 28, 2008–June 2, 2009	0.027199
		June 3, 2009–July 28, 2011	0.013864
		July 29, 2011–Dec 18, 2011	0.026529
		Dec 19, 2011–June 23, 2013	0.010711
		June 24, 2013–Oct 6, 2014	0.008040
		Oct 7, 2014–Nov 30, 2016	0.015793
		Dec 1, 2016–Jan 24, 2018	0.008434
		Jan 25, 2018–Feb 19, 2020	0.013402
		Feb 20, 2020–March 31, 2021	0.037720
Health	2	April 1, 2006–Feb 20, 2020	0.010508
		Feb 21, 2020–April 5, 2020	0.045509
		April 6, 2020–March 31, 2021	0.011446
Consumer	5	April 1, 2006–July 5, 2007	0.005571
		July 6, 2007–Sept 14, 2008	0.009065
		Sept 15, 2008–Nov 27, 2008	0.032355
		Nov 28, 2008–Jan 27, 2009	0.013164
		Jan 28, 2009–March 19, 2009	0.018389
		March 20, 2009–March 31, 2021	0.008763

Table 2 (continued)

Series	Break points	Time period	SD
Industrial	12	April 1, 2006–Aug 15, 2006	0.009330
		Aug 16, 2006–July 24, 2007	0.006857
		July 25, 2007–Sept 11, 2008	0.014568
		Sept 12, 2008–Dec 1, 2008	0.043556
		Dec 2, 2008–May 31, 2009	0.027736
		June 1, 2009–Nov 8, 2009	0.014692
		Nov 9, 2009–July 24, 2011	0.012296
		July 25, 2011–Dec 19, 2011	0.023565
		Dec 20, 2011–Aug 17, 2015	0.008661
		Aug 18, 2015–July 7, 2016	0.011466
		July 8, 2016–Jan 30, 2018	0.006256
		Feb 1, 2018–Feb 25, 2020	0.011095
		Feb 26, 2020–March 31, 2021	0.024285

Time periods detected by modified ICSS algorithm. Sample period is from April 1, 2006 to March 31, 2021

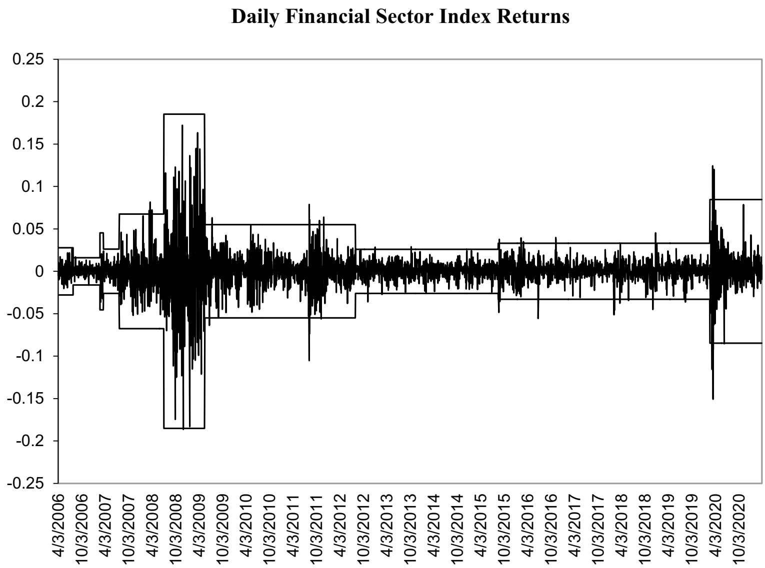

Fig. 1 Daily financial sector index returns. *Note* Bands drawn at ± 3 standard deviations and volatility breaks are identified by modified ICSS algorithm

ignored then volatility spillover effects are exaggerated due to a bias which is present in popular bivariate GARCH models. This lack of volatility spillover across sectors could also be due to hedging performed by investors across markets.

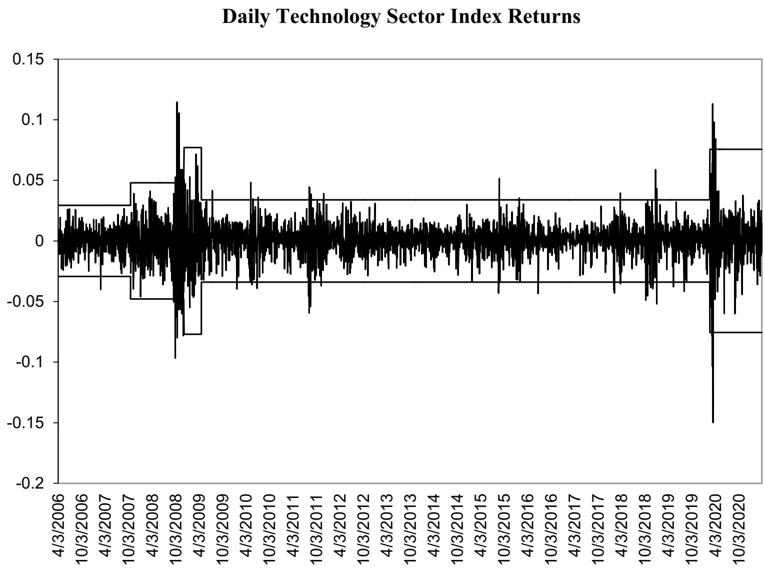

Fig. 2 Daily technology sector index returns. *Note* Bands drawn at ± 3 standard deviations and volatility breaks are identified by modified ICSS algorithm

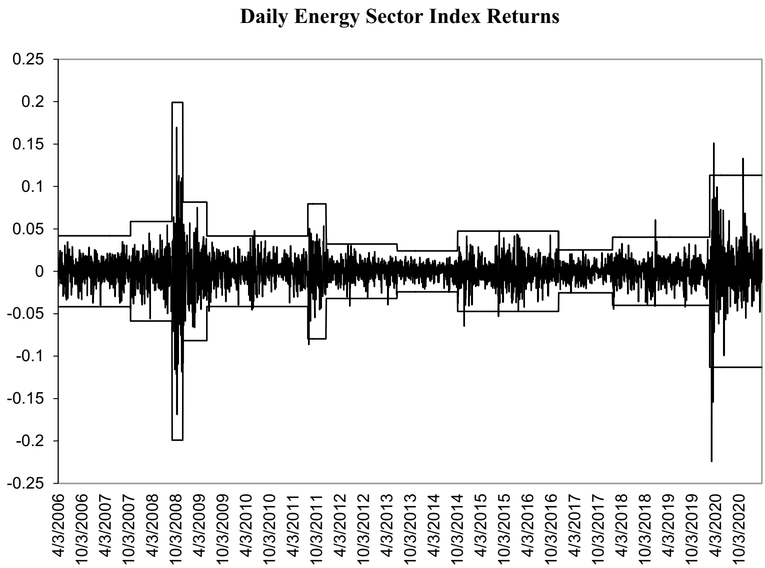

Fig. 3 Daily energy sector index returns. *Note* Bands drawn at ± 3 standard deviations and volatility breaks are identified by modified ICSS algorithm

I also conduct more analysis to see if my above findings carry over to other sector combinations. Consequently, I model the financial and energy sector. The results ignoring breaks are presented in Panel A of Table 4 while results after accounting for

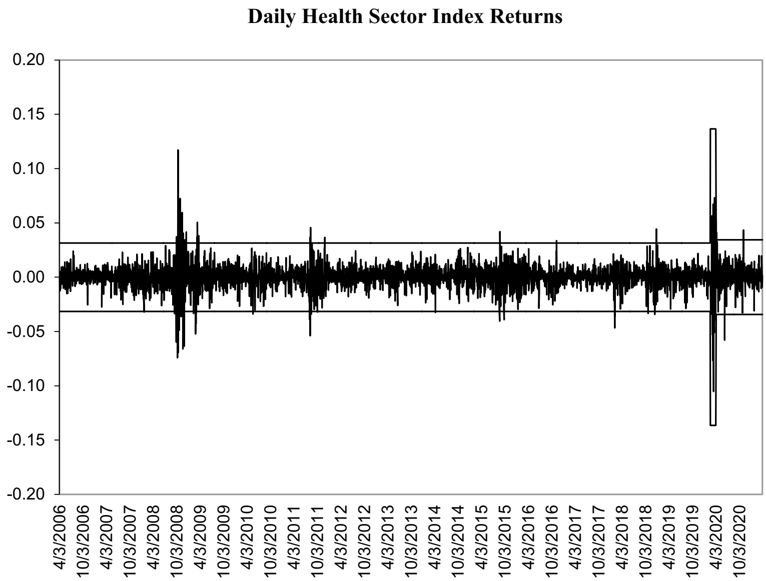

Fig. 4 Daily health sector index returns. *Note* Bands drawn at ± 3 standard deviations and volatility breaks are identified by modified ICSS algorithm

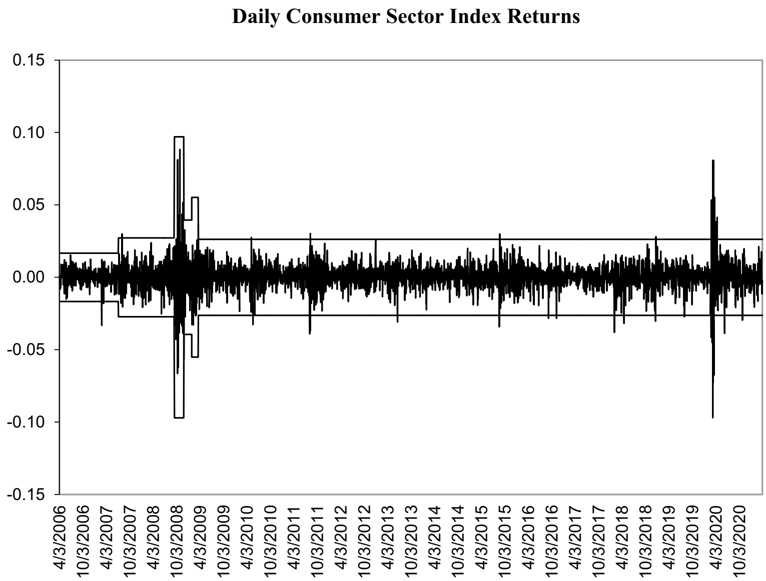

Fig. 5 Daily consumer sector index returns. *Note* Bands drawn at ± 3 standard deviations and volatility breaks are identified by modified ICSS algorithm

breaks are shown in Panel B of Table 4. I find same results as reported earlier; that is ignoring breaks show significant bidirectional volatility spillover effects and once breaks are accounted for then I find unidirectional volatility spillover effects. Table 5

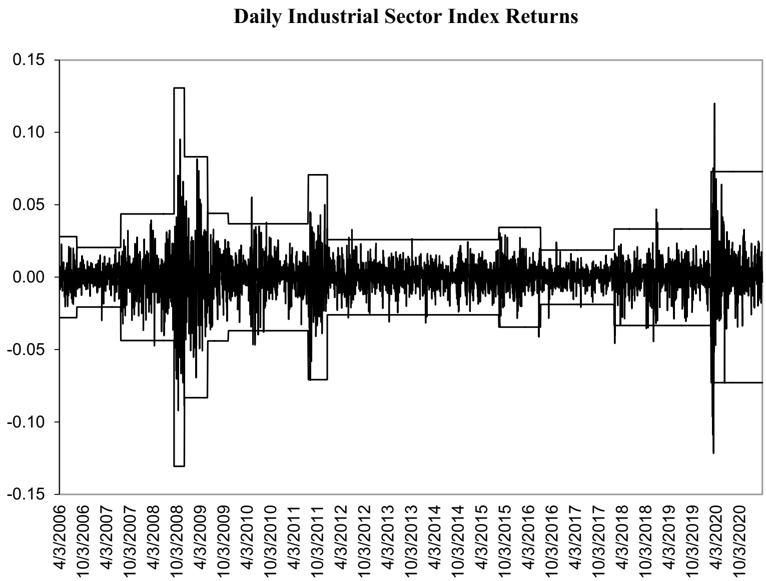

Fig. 6 Daily industrial sector index returns. *Note* Bands drawn at ± 3 standard deviations and volatility breaks are identified by modified ICSS algorithm

Table 3 (A) Bivariate GARCH model without volatility breaks for financial and technology Sector and (B) bivariate GARCH model with volatility breaks for financial and technology Sector

Panel A

Financial sector variance equation

$$h_{11,t+1} = 5.99 \times 10^{-8} + 1.848h_{11,t} - 2.855h_{12,t} + 1.102h_{22,t} + 0.063\varepsilon_{1,t}^2 + 0.026\varepsilon_{1,t}\varepsilon_{2,t} + 0.002\varepsilon_{2,t}^2$$

(0.35) (25.10) (– 6.56) (3.68) (3.15) (1.72) (0.71)

Technology sector variance equation

$$h_{22,t+1} = 2.14 \times 10^{-6} + 0.775h_{11,t} - 2.363h_{12,t} + 1.801h_{22,t} + 0.002\varepsilon_{1,t}^2 - 0.035\varepsilon_{1,t}\varepsilon_{2,t} + 0.112\varepsilon_{2,t}^2$$

(8.77) (5.14) (– 10.44) (24.51) (0.89) (– 1.47) (3.83)

Panel B

Financial sector variance equation

$$h_{11,t+1} = 1.62 \times 10^{-6} + 0.928h_{11,t} - 0.089h_{12,t} + 0.002h_{22,t} + 0.063\varepsilon_{1,t}^2 + 0.064\varepsilon_{1,t}\varepsilon_{2,t} + 0.016\varepsilon_{2,t}^2$$

(2.73) (42.01) (– 4.92) (2.55) (3.51) (6.84) (2.50)

Technology sector variance equation

$$h_{22,t+1} = 4.93 \times 10^{-6} + 2.34 \times 10^{-7}h_{11,t} + 0.0008h_{12,t} + 0.843h_{22,t} + 0.0001\varepsilon_{1,t}^2 + 0.007\varepsilon_{1,t}\varepsilon_{2,t} + 0.116\varepsilon_{2,t}^2$$

(8.18) (0.01) (0.03) (36.24) (0.13) (0.26) (4.52)

h_{11} denotes volatility of financial sector returns and h_{22} denotes volatility of technology sector returns. T-values are reported beneath the coefficients. $LR = 2\left[L\left(\Theta_1\right) - L\left(\Theta_0\right)\right]$, where $L\left(\Theta_1\right)$ and $L\left(\Theta_0\right)$ are the maximum log likelihood values attained from the model with and without volatility breaks, respectively. Thus LR is calculated as 2 (23,815.44 − 23,625.69) = 379.5, which is significant at 1% level suggesting that the model with breaks gives a significantly better fit

Table 4 (A) Bivariate GARCH model without volatility breaks for financial and energy sector and (B) bivariate GARCH model with volatility breaks for financial and energy sector

Panel A

Financial sector variance equation

(3.36) (6.31) (– 12.15) (15.94) (3.66) (– 8.87) (3.95)

Energy sector variance equation

$$h_{22,t+1} = 5.08 \times 10^{-6} + 0.139h_{11,t} + 0.681h_{12,t} + 0.832h_{22,t} + 0.0009\varepsilon_{1,t}^{2} + 0.006\varepsilon_{1,t}\varepsilon_{2,t} + 0.012\varepsilon_{2,t}^{2}$$

(2.02) (4.36) (9.69) (38.84) (0.65) (1.20) (1.99)

Panel B

Financial sector variance equation

$$h_{11,t+1} = 1.23 \times 10^{-6} + 0.627h_{11,t} + 0.140h_{12,t} + 0.007h_{22,t} + 0.056\varepsilon_{1,t}^{2} - 0.258\varepsilon_{1,t}\varepsilon_{2,t} + 0.2966\varepsilon_{2,t}^{2}$$

(1.44) (7.07) (2.26) (1.28) (2.90) (– 3.52) (3.92)

Energy sector variance equation

$$h_{22,t+1} = 4.47 \times 10^{-6} + 0.020h_{11,t} - 0.270h_{12,t} + 0.911h_{22,t} + 0.034\varepsilon_{1,t}^{2} + 0.013\varepsilon_{1,t}\varepsilon_{2,t} + 0.001\varepsilon_{2,t}^{2}$$

(5.23) (2.09) (– 4.27) (24.71) (2.18) (0.48) (0.26)

h_{11} denotes volatility of financial sector returns and h_{22} denotes volatility of energy sector returns. T-values are reported beneath the coefficients. $LR = 2\left[L(\Theta_1) - L(\Theta_0)\right]$, where $L(\Theta_1)$ and $L(\Theta_0)$ are the maximum log likelihood values attained from the model with and without volatility breaks, respectively. Thus LR is calculated as 2 (21,529.07 – 21,481.83) = 94.48, which is significant at 1% level suggesting that the model with breaks gives a significantly better fit

Table 5 (A) Bivariate GARCH model without volatility breaks for technology and energy sector and (B) bivariate GARCH model with volatility breaks for technology and energy sector

Panel A

Technology sector variance equation

(1.02) (3.66) (6.88) (16.75) (0.12) (– 0.25) (8.83)

Energy sector variance equation

$$h_{22,t+1} = 1.14 \times 10^{-5} + 1.42h_{11,t} - 0.882h_{12,t} + 0.136h_{22,t} + 0.022\varepsilon_{1,t}^{2} + 0.012\varepsilon_{1,t}\varepsilon_{2,t} + 0.001\varepsilon_{2,t}^{2}$$

(3.52) (15.37) (– 11.85) (5.25) (1.27) (1.19) (0.77)

Panel B

Technology sector variance equation

$$h_{11,t+1} = 3.21 \times 10^{-5} + 0.151h_{11,t} - 0.120h_{12,t} + 0.023h_{22,t} + 0.0003\varepsilon_{1,t}^{2} - 0.022\varepsilon_{1,t}\varepsilon_{2,t} + 0.372\varepsilon_{2,t}^{2}$$

(5.60) (3.52) (– 3.09) (1.61) (0.20) (– 0.40) (17.36)

Energy sector variance equation

$$h_{22,t+1} = 1.96 \times 10^{-6} + 0.322h_{11,t} + 1.00h_{12,t} + 0.781h_{22,t} + 0.001\varepsilon_{1,t}^{2} + 0.003\varepsilon_{1,t}\varepsilon_{2,t} + 0.002\varepsilon_{2,t}^{2}$$

(0.34) (2.90) (7.02) (13.14) (0.42) (0.63) (0.67)

h_{11} denotes volatility of technology sector returns and h_{22} denotes volatility of energy sector returns. T-values are reported beneath the coefficients. $LR = 2\left[L(\Theta_1) - L(\Theta_0)\right]$, where $L(\Theta_1)$ and $L(\Theta_0)$ are the maximum log likelihood values attained from the model with and without volatility breaks, respectively. Thus LR is calculated as 2 (22,275.94 – 22,181.88) = 94.06, which is significant at 1% level suggesting that the model with breaks gives a significantly better fit

Table 6 (A) Bivariate GARCH model without volatility breaks for health and industrial sector and (B) bivariate GARCH model with volatility breaks for health and industrial sector

Panel A

Health sector variance equation

(5.74) (25.04) (− 38.61) (42.44) (4.30) (4.16) (1.55)

Industrial sector variance equation

$$h_{22,t+1} = 2.88 \times 10^{-6} + 0.286h_{11,t} + 0.601_{12,t} + 0.316h_{22,t} + 0.0004\varepsilon_{1,t}^{2} + 0.014\varepsilon_{1,t}\varepsilon_{2,t} + 0.102\varepsilon_{2,t}^{2}$$

(4.50) (16.33) (66.85) (16.13) (0.409) (0.85) (6.70)

Panel B

Health sector variance equation

$$h_{11,t+1} = 3.51 \times 10^{-5} + 0.376h_{11,t} - 1.299h_{12,t} + 1.121h_{22,t} + 0.060\varepsilon_{1,t}^{2} + 0.032\varepsilon_{1,t}\varepsilon_{2,t} + 0.004\varepsilon_{2,t}^{2}$$

(7.94) (2.86) (− 4.71) (12.77) (4.62) (3.46) (1.36)

Industrial sector variance equation

$$h_{22,t+1} = 2.53 \times 10^{-6} + 0.260h_{11,t} + 0.591h_{12,t} + 0.335h_{22,t} + 0.0009\varepsilon_{1,t}^{2} + 0.019\varepsilon_{1,t}\varepsilon_{2,t} + 0.098\varepsilon_{2,t}^{2}$$

(5.77) (1.82) (11.90) (2.60) (0.56) (1.17) (7.65)

h_{11} denotes volatility of health sector returns and h_{22} denotes volatility of industrial sector returns. T-values are reported beneath the coefficients. $LR = 2[L(\Theta_1) - L(\Theta_0)]$, where $L(\Theta_1)$ and $L(\Theta_0)$ are the maximum log likelihood values attained from the model with and without volatility breaks, respectively. Thus LR is calculated as 2 (25,383.36 – 25,370.25) = 26.22, which is significant at 1% level suggesting that the model with breaks gives a significantly better fit

Table 7 (A) Bivariate GARCH model without volatility breaks for health and consumer sector and (B) bivariate GARCH model with volatility breaks for health and consumer sector

Panel A

Health sector variance equation

$$h_{11,t+1} = 9.03 \times 10^{-6} + 0.046h_{11,t} - 0.275h_{12,t} + 0.407h_{22,t} + 0.0007\varepsilon_{1,t}^{2} + 0.046\varepsilon_{1,t}\varepsilon_{2,t} + 0.762\varepsilon_{2,t}^{2}$$

(3.15) (2.45) (− 4.61) (6.27) (0.315) (0.63) (15.22)

Consumer sector variance equation

$$h_{22,t+1} = 9.21 \times 10^{-6} + 0.420h_{11,t} + 0.771h_{12,t} + 0.353h_{22,t} + 0.0005\varepsilon_{1,t}^{2} - 0.001\varepsilon_{1,t}\varepsilon_{2,t} + 0.001\varepsilon_{2,t}^{2}$$

(3.22) (9.11) (12.11) (6.14) (0.46) (− 0.67) (0.50)

Panel B

Health sector variance equation

$$h_{11,t+1} = 2.71 \times 10^{-5} + 0.022h_{11,t} + 0.006h_{12,t} + 0.0004h_{22,t} + 0.001\varepsilon_{1,t}^{2} + 0.063\varepsilon_{1,t}\varepsilon_{2,t} + 1.010\varepsilon_{2,t}^{2}$$

(22.88) (2.00) (0.26) (0.13) (0.38) (0.76) (26.08)

Consumer sector variance equation

$$h_{22,t+1} = 1.06 \times 10^{-7} + 0.138h_{11,t} - 0.659h_{12,t} + 0.782h_{22,t} + 0.001\varepsilon_{1,t}^{2} - 0.001\varepsilon_{1,t}\varepsilon_{2,t} + 0.0005\varepsilon_{2,t}^{2}$$

(0.08) (3.54) (− 9.25) (13.44) (0.74) (− 0.46) (0.24)

h_{11} denotes volatility of health sector returns and h_{22} denotes volatility of consumer sector returns. T-values are reported beneath the coefficients. $LR = 2[L(\Theta_1) - L(\Theta_0)]$, where $L(\Theta_1)$ and $L(\Theta_0)$ are the maximum log likelihood values attained from the model with and without volatility breaks, respectively. Thus LR is calculated as 2 (25,896.93 – 25,789.88) = 214.10, which is significant at 1% level suggesting that the model with breaks gives a significantly better fit

Table 8 (A) Bivariate GARCH model without volatility breaks for industrial and consumer sector and (B) bivariate GARCH model with volatility breaks for industrial and consumer sector

Panel A

Industrial sector variance equation

$h_{11,t+1} = 6.90 \times 10^{-6} + 0.340_{11,t} + 0.686h_{12,t} + 0.346h_{22,t} + 0.00001\varepsilon^2_{1,t} + 0.008\varepsilon_{1,t}\varepsilon_{2,t} + 1.10\varepsilon^2_{2,t}$

(1.80) (3.42) (5.68) (6.46) (0.05) (0.10) (5.13)

Consumer sector variance equation

$h_{22,t+1} = 8.33 \times 10^{-6} + 0.089h_{11,t} - 0.463h_{12,t} + 0.603h_{22,t} + 0.018\varepsilon^2_{1,t} + 0.022\varepsilon_{1,t}\varepsilon_{2,t} + 0.006\varepsilon^2_{2,t}$

(2.18) (4.85) (– 11.57) (13.31) (1.76) (1.87) (1.15)

Panel B

Industrial sector variance equation

$h_{11,t+1} = 1.84 \times 10^{-5} + 0.059h_{11,t} - 0.075h_{12,t} + 0.024h_{22,t} + 0.00002\varepsilon^2_{1,t} - 0.013\varepsilon_{1,t}\varepsilon_{2,t} + 1.64\varepsilon^2_{2,t}$

(5.63) (2.60) (– 1.12) (0.58) (0.06) (– 0.13) (21.95)

Consumer sector variance equation

$h_{22,t+1} = 1.34 \times 10^{-6} + 0.124h_{11,t} + 0.608h_{12,t} + 0.743h_{22,t} + 0.0005\varepsilon^2_{1,t} - 0.0005\varepsilon_{1,t}\varepsilon_{2,t} + 0.0001\varepsilon^2_{2,t}$

(0.41) (4.60) (13.21) (9.39) (0.53) (– 0.31) (0.17)

h_{11} denotes volatility of industrial sector returns and h_{22} denotes volatility of consumer sector returns. T-values are reported beneath the coefficients. $LR = 2[L(\Theta_1) - L(\Theta_0)]$, where $L(\Theta_1)$ and $L(\Theta_0)$ are the maximum log likelihood values attained from the model with and without volatility breaks, respectively. Thus LR is calculated as 2 (25,054.05 – 24,969.35) = 169.40, which is significant at 1% level suggesting that the model with breaks gives a significantly better fit

shows the results for the technology and energy sector and I confirm the same results as well. Specifically, I find bidirectional volatility spillover if breaks are ignored and unidirectional spillover results if breaks are adjusted for in the model. These same results carry over to other sector combinations such as health and industrial (Table 6), health and consumer (Table 7) and industrial and consumer (Table 8).

The significance of structural breaks in volatility can be additionally tested by the commonly used likelihood ratio (LR) statistic, which is computed as $LR = 2[L(\Theta_1) - L(\Theta_0)]$, where $L(\Theta_1)$ and $L(\Theta_0)$ are values acquired via maximum log-likelihood from the GARCH model with and without volatility breaks, respectively. This statistic has a distribution given by χ^2 where the degrees of freedom equal the number of constraints imposed in the model with breaks relative to the model without breaks and this statistic is reported in the notes of each table of the bivariate GARCH estimation results. As can be seen, in all cases, the null hypothesis of no change in volatility can be rejected at the 1% level of significance. This implies that, in all three cases, the model with volatility breaks provides a significantly better fit relative to the model without breaks.

Finally, I did the standard series of diagnostics on residuals on both set of models (with and without breaks) for each sector combination (results not report for the sake of brevity but can be provided on request). It is pertinent to note that no issues were identified in all cases. This highlights the significance of explicitly testing for volatility breaks in the underlying return series before modelling as normal residual diagnostics are not able to identify any problems.

5 Economic implications: hedge ratios

Investors and policy makers want to know if shocks and volatility spillover exist across different sectors so they can make optimal decisions. There are many practical economic implications of my results as accurately estimating volatility is vital for decisions involving pricing of financial assets, risk management and portfolio allocation (see Kroner and Ng, 1998). In the interest of space, here I only focus on the impact that breaks have on estimated optimal hedge ratios. Lien and Yang (2010) show that risk exposure in currencies can be optimally hedged using currency futures if breaks in unconditional variance are accounted for in a bivariate GARCH framework. Consequently, proper estimation of volatility spillover is required for making correct hedging decisions.

Hedging across markets is widely practiced in real life by investors to minimize their risk exposure. Kroner and Sultan (1993) argue that an investor should short \$β of asset 1 to minimize risk of a \$1 portfolio that have a long position in asset 2. The time-variant hedge ratio β is computed as $\beta_t = \frac{h_{12t}}{h_{22t}}$, where h_{12t} is the conditional covariance between asset 1 and asset 2 while h_{22t} is the conditional variance of asset 2 returns. As can be seen that this hedge ratio is dependent on how volatility spillover across assets evolves over time and clearly incorrectly estimating the volatility spillover will give poor hedging efficiency. Since cross market hedging is typically conducted using two assets which are positively correlated, so I use financial and technology sector in my example.[6] I find that the average estimated hedge ratio ignoring the volatility break was 0.37 with a standard deviation of 0.97, but after accounting for breaks you get a hedge ratio of 0.77 with a standard deviation of 0.26. These results show that not only hedge ratios change substantially in the presence of breaks but ignoring them results in far greater variability. It is important to note that that more variability in estimated hedge ratios can potentially result in a significant increases in portfolio rebalancing costs as traders need to adjust their portfolio more frequently. It is documented in the literature that large variability in the estimated hedge ratios results in poor hedging performance as compared to a simple unconditional (constant) hedge ratio (see Fan et al., 2016; Lien, 2010). My findings are in line with simulation results of Caporin and Malik (2020) as they show that structural breaks induce changes in estimated hedge ratios and the resulting ratios shows more variability.

6 Monte Carlo simulations

In this section, I extend the work of Caporin and Malik (2020) by using Monte Carlo simulations and showing that ignoring structural breaks induces spurious spillover effect. I also show that adding a dummy variable eliminates this bias as that is the strategy I use in my earlier empirical analysis.[7]

I generate two univariate GARCH series using $h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}$, each with $\omega = 0.000008$, $\alpha = 0.1$ and $\beta = 0.85$. This gives us an annual variance of 20%. These values are in line with the US stock market over the last 15 years of daily data. Then I induce a

[6] Other sector combinations gave same overall conclusion that after accounting for breaks the hedge ratios change substantially and exhibit less variability.

[7] I only discuss the base model of simulations here in the interest of space and detailed simulation results are available on request.

break in the middle of the sample (by increasing ω to 0.000032) such that in the second half of sample, variance doubles to 40%. This variance break size magnitude is typical of variance breaks that I found in the US stock market over the last 15 years of daily data. I use an overall sample size of 4000, which gives us 2000 observations on each side so we do not have to be concerned about the small sample bias. I use RATS software to estimate MGARCH by using 20 initial iterations of simplex algorithm then switching to BFGS algorithm. This is the standard way most researchers estimate MGARCH models. Using 5000 simulations, I found that the b_{21} and b_{12} element of BEKK parameters from Eqs. (3) and (4) was statistically significant 30% of the time using robust standard errors. This shows that researchers would find spurious volatility spillover 30% of the time although both series are generated independently. It is interesting to note that other simulations showed (not reported here) that bias substantially increases when I incorporate correlation among series, break size is increased or multiple breaks are incorporated.

Finally, I re-estimate the same model 5000 times on the simulated returns with structural breaks but augment my model with dummy variable corresponding to the induced break point, replicating my approach in my earlier empirical analysis. I found the spurious volatility spillover effect to reduce from 30 to 1%, which is equal to the level of significance I used. These numbers show that adding dummy variable to account for structural breaks in volatility yields correct estimate for the volatility spillover effect.[8]

7 Conclusion

This paper studies volatility spillover between major US equity sector returns utilizing bivariate GARCH models using daily data from April 2006 to March 2021. The modified ICSS algorithm is employed to identify significant structural breaks in volatility in sector index returns. My results show significant volatility spillover in *both* directions in each of the six estimated bivariate GARCH models if volatility breaks are ignored. However, after adjusting for structural breaks in volatility, I find significantly less volatility spillover effects and only one sector affects volatility of the other. I also report that average hedge ratios dramatically change and show less variability when volatility breaks are added in the bivariate GARCH model. The evidence suggests that my findings are possibility driven by cross-sector hedging by investors and possibly due to an estimation bias in the bivariate GARCH models because they typically overestimate the degree of volatility spillovers in the presence of structural breaks.

As quite a few financial assets are traded in the market based on these sector indexes, it is important that investors and policy makers make an accurate estimate of the extent of the volatility spillover that exists across these major sectors returns over time. I make a timely contribution as the importance of volatility spillover effects across financial markets have taken center stage due to the impact that the looming COVID-19 crisis has on financial markets across the globe.

[8] It is pertinent to note that Caporin and Malik (2020) primarily report their findings using the Wald Test but also show that their results hold even if they use a Lagrange Multiplier test.

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