Foreign-Listing: A Strategy for Improving Performance for Firms from Emerging Economies

Olakunle Akinola[*] & Kolo Ruth [**]
Department of Entrepreneurship and Business Studies,
Federal University of Technology, Minna, Niger State
*akolaks@futminna.edu.ng, Mobile number: +23481-854-144-17
**ruth.kolo@futminna.edu.ng

Abstract
This study examined the exposure of cross-listed firms to market risk and its impact on the firm's stock return for firms from emerging economic group cross-listed on the London Stock Exchange. The study sought to determine if there is a negative asymmetry risk exposure on stock returns and a spillover effect of the economic policy uncertainty from the U.S. impacting negatively on the stock returns of the cross-listed firms. In carrying out the analysis, secondary data was used by collecting individual firms daily stock prices from Bloomberg database to determine firms monthly stock returns while the economic policy uncertainty index was downloaded from www.policyuncertianty.com. The period of analysis spanned from year 2000 to 2020 and the Dynamic Conditional Correlation Generalised Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model was employed for analysis. Based on findings economic policy uncertainty is a major source of structural breaks that has a detrimental effect on the overall performance of firms from the emerging economic group of countries. Therefore, firms from the emerging group of countries must consider the stability and volatility in their proposed listing market before deciding to list in a foreign market.

Keywords: Cross-listing, Economic Policy, Uncertainty, Structural Breaks, Stock Returns

Introduction
The decision of firms to cross-list their shares outside their domestic market in search of increased capital flow to improve their liquidity position and firm value has improved significantly with the advent of globalization which has lowered capital restriction and resulted in the growth of global financial markets. This reduction in restriction of cross-border capital flows have resulted in improved information flows enabling securities markets to compete on a global scale. This trend has propelled firms from both emerging and developing economies to cross-list their shares in more liquid developed stock markets to raise capital and improve their over-all performance.

The underlining motivation and cost-benefit of firms listing outside of their home market has generated significant research interest with analysis focused on the firms' growth (Benos & Weisbach, 2004; Karolyi, 2006; Pagano et al., 2002), firms improved visibility (Ying et al., 2015); lower cost-of-capital (Errunza & Miller, 2000); and improved firm value (Cetorelli & Peristiani, 2015). The negative impact of globalization however within the last decade reflected in the global financial crisis (i.e., Brexit in 2016, the China-US trade war since 2018, the Covid-19 epidemic in 2020, and the Ukraine war since 2022) has subjected the world economies to substantial shocks, giving rise to rising Global Economic Policy Uncertainty Index and contributing to increased policy uncertainty (Andrikopoulos, et al., 2023) across world economies. Also, domestic policy uncertainty has had a detrimental influence on international capital flows, according to recent studies by Gauvin et al. (2014) and Julio and Yook (2016).

Given this trend international capital flows are now a major avenue for transferring risks between economies due to the growing financial integration.

However, liquidity in developed stock exchanges has remained a major attraction for firms from emerging and developing economies listing on these exchanges. Firms searching for a cheaper source of capital tend to list on a more liquid foreign exchange to raise additional capital to support their expansion programmes, operations, and investment drives. Hence, cross-listing constantly exposes such firms to certain systematic risks. It is therefore imperative to examine the inherent advantages of cross-listing in more developed markets for firms from developing and emerging economies, given the systematic risk to which the firms are exposed.

The following objectives have been identified for the research work. First, the research aims to determine if cross-listed firms from emerging markets listed on the developed economies' stock exchanges experience a lower negative asymmetry risk exposure when compared to their domestic counterparts. Secondly, the research work seeks to assess if foreign listed firms from emerging economies experience less negative asymmetry risk exposure on stock returns when compared to their industry peers in the listed foreign market. Thirdly, the research work investigates the influence of economic policy uncertainty (EPU) in the United States (U.S.) economy and its negative impact on the stock returns of cross-listed firms in their domestic market.

The study contributes to extending literature in international financial asset pricing theory from an emerging market perspective by providing an impact analysis of systematic risk using EPU as a proxy for market exposures on cross-listed firms. It is observed that growing attention in the literature is now devoted to evaluating the price of financial assets and the important role played by uncertainty as macroeconomic uncertainty is directly linked to changes in asset prices (Drechsler, 2013; Su et al., 2019). Previous studies (see Balli et al. 2021; Ma, & Ng; 2018, Ozturk & Sheng, 2018; Sua, Fanga, & Yin, 2019; Su et al., 2019) have identified factors influencing firm’s stock returns based on macroeconomic variables; however, the focus was on listed firms which is an aggregation of both cross-listed and non-cross-listed firms. Hence, this study presents an opportunity to assess whether cross-listed firms’ behaviour aligns with previous research findings. Lastly, this study focuses on the influence of economic policy uncertainty on individual firm's stock returns moved a step further by analysing the effect of macroeconomic variables on firms. Previous studies have primarily focused on stock market excess return (see Asgharian et al., 2015; Chuliá, et al., 2017; Pan et al., 2017; Phan et al., 2018; Su et al., 2019). To the best of our knowledge, this study is the first to examine macroeconomic variables using EPU for individual firms' stock returns. The analysis will focus on countries in the Emerging Economies Group (EEG) cross-listed on the London Stock Exchange (LSE).

Literature Review

In the world of finance, market risk and stock returns are fundamental ideas that are extremely important and have a significant impact on investing choices of firms. One of the fundamental decision considerations that firms make in deciding the choice of stock market to cross-list is the inherent turbulence and volatility of the market. This is because firms are aware of the influence of economic policy uncertainty in different economies which could impact on their stock return. Firm's exposure to market risk occurs due to a negative occurrence in any country's macro-economy, resulting in adverse effect on the stock market to which listed firms have no influence in mitigating such impact on their traded stock. Market risk, therefore, exposes cross-listed firms to additional risk in the listed market. This is because financial markets in which these firms trade experience high volatility during such structural breaks. An example of such periods is the Eurozone debt crisis in 2008 and the global financial crisis of 2007 - 2008; the impact of Brexit on traded stock on the London Stock Exchange (LSE), and the negative economic impact of the Covid-19 pandemic resulting in an oil trade war between Russia – Saudi Arabia in March 2020 and the recent invasion of Ukraine by Russia in 2022 which has led to the spike in crude oil prices. Hence, firms are fully aware that stock exchanges are not immune against structural breaks and uncertainties in the economies where they operate, and their operating performance impacted either negatively or positively.

The theoretical explanations that accounts for the correlation between uncertainty and investment has been examined within the framework of option value, of waiting and the risk aversion theory. The option value of waiting theory supports the negative investment-uncertainty link. Dixit and Pindyck (1994) developed this idea in their orthodox investment theory to explain the uncertainty-investment linkage. Dixit and Pindyck stated that the option value of waiting helps explain the negative association between uncertainty and investment. This perspective acknowledges waiting for improved, information before firms takes investment decisions. Uncertainty reduces corporate investment, at least temporarily in the short run. Uncertainty they argued creates risk and ambiguity, making corporations cautious and prone to wait for better economic conditions before investing. Carrière-Swallow, and Céspedes (2013) however argued that the value of waiting is also influenced by stochastic discount factor, which firms use to discount future gains. When the future is heavily discounted, the value of postponing decision to cross-list to await market stability reduces. As a result, firms are more likely to proceed with the decision to cross-list even in the face of considerable uncertainty. Discount rate differences between countries may explain some of the variances in the magnitude of this effect and reason for choice of destination market to cross-list by firms.

The level of risk aversion that investors possess is a crucial factor in international investment. According to Gauvin et al. (2014), when the level of uncertainty increases, which indicates an increase in the likelihood of unforeseen risks, investors have a tendency to reduce the amount of money they put into cross-border investments. Risk-averse organisations may potentially induce investment uncertainty. According to Zeira (1990) and Nakamura (1999), enterprises' risk-aversion negatively impacts their investment behaviour. Nakamura (1999) developed a model that showed uncertainty–investment linkages are negative. When relative risk aversion exceeds output labour elasticity, Nakamura's model predicted a negative uncertainty–investment relationship. Due to pricing or cost uncertainty, risk-averse investors and corporations will restrict investment spending. Another element to consider is the negative association between return on investment and global economic policy uncertainty (Hoque & Zaidi, 2018). According to research, a rise in policy uncertainty in the United States reduces portfolio inflows to emerging countries (Gauvin et al., 2014). In conclusion, when global economic policy uncertainty rises, private investment tends to fall, as even moderate levels of uncertainty can be a considerable deterrent to investment (Rodrik, 1991).

Empirical findings have analysed the conditional volatility that evolves because of these structural brakes on the financial market as the markets have reacted both negatively and positively (Chuliá et al. 2017) to structural breaks over time, leading to portfolio rebalancing (Mensi et al., 2014; Zhang et al., 2013). Hence, examining cross-listed firms' stock volatility during these structural breaks will enable the researcher investigate firms' risk exposure and determine if firms' risk exposure is reduced or increased by cross-listing. Different scholars have examined the correlation of the risk-return volatility relations in finance literature using various risk measures, such as economic policy uncertainty (Baker et al., 2016; Balli, et al. 2021; Sua et al., 2019), macroeconomy uncertainty (MEU) (Ludvigson et al., 2018; Ozturk &

Sheng, 2018), equity market uncertainty (EMU), and equity market volatility (EMV) (Balli et al., 2021). A significant part of this literature has focused on the influence of global financial crisis (GFC), originating from the U.S. stock markets and its attendant spillover effect on other markets (for both emerging and developed economies) (Ahmad et al., 2013; Bekaert et al., 2014; Chiang et al., 2013; Hwang et al., 2013; Mensi et al., 2016, 2017).

In a study by Mensi et al. (2016), the contagion effect of the U.S. stock market on BRICS (i.e., Brazil, Russia, India, China, and South Africa) countries was examined based on the GFC of 2007 to 2008 that originated in the U.S. market. In carrying out the analysis to determine the volatility spillover and structural breaks, Mensi et al. (2016) employed the use of bivariate dynamic conditional correlation fractionally integrated generalised autoregressive conditional heteroscedastic (DCC-FIGARCH) model, Value-at-Risk (VaR) and modified iterative cumulative sum of squares (ICSS) algorithm. Their results revealed a significant asymmetry and long memory conditional volatility between the U.S. market and the BRICS countries' stock markets. On the other hand, Abbas, Khan, & Ali Shah (2013) investigated the possibility of a contagion effect among three developed stock markets (i.e., U.S, U.K, & Singapore) and four Asian equities markets (i.e., Pakistan, China, India, & Sri Lanka) and found significant volatility spillover between countries with economic and trading ties in the different regions examined. Additionally, based on the GFC of 2008–2009, Hammoudeh et al. (2016) also looked at the volatility spillover effect between the U.S. and European markets on the BRICS markets using the dynamic conditional equi-correction fractional integrated asymmetric power (DECO-FISPSRCH). They observed an increased correlation between the U.S., European stock markets and the BRICS stock markets.

Chuliá, et al. (2017), on the other hand, noted the limitations inherent in previous studies carried out, which tilted towards conditional mean-based models. To predict the volatility spillover effect with more accuracy, they introduced the quantile causality in examining the impact of EPU and EMU on stocks in the financial market. They, however, acknowledged the limitation inherent in their approach, which is the inability of their model to provide information on the direction and persistence of the impact of uncertainty being measured. Su et al. (2019) on the other hand focused on the use of EPU, financial uncertainty (F.U.), and news implied uncertainty (NIU) as the index for measuring the volatility spillover effect of the U.S. financial market on emerging markets. The spillover effect was analysed by adopting the generalised autoregressive conditional heteroskedasticity mixed data sampling (GARCH-MIDAS) model which is a crucial index used for analysis, is at best released quarterly. At the same time, other key variables are measured on a daily, weekly, or monthly basis. Thus, the GARCH-MIDAS model helped avoid any loss of information that could have occurred if the GARCH or realised volatility model had been employed (Pan et al., 2017).

Furthermore, Phan et al. (2018) went a step further by analysing the industry effect of EPU and the country effect carried out in previous studies using data from 16 countries. They reported a positive correlation between EPU and stock returns with varying impacts on firms' stocks based on their industry. They observed that some sectors were more negatively affected than others based on their evaluation of the effects of GFC on stock return.

The studies above indicate that any structural breaks experienced in the American market have a spillover effect on other financial markets across the globe. It has been observed that the U.S. stock market has been the focal point for examining GFC, EPU, EMU, F.U. and NIU. This can be attributed to the size effect of the U.S. stock market and U.S. global dominance. As a result, it is believed that the U.S. stock market has an impact on stock markets around the world.

Given the analysis above, previous literature has traditionally focused on studying structural breaks in the financial markets and their impact on stock returns using indexes such as GFC, EPU, F.C., EMU, NIU, and MUI. It is noted that these analyses have been country-based, except for the work of Phan et al. (2018), who carried out a sectoral analysis. Also, none of these investigations has carried out an impact assessment on cross-listed firms. Hence, investigating the impact of market risk based on EPU for cross-listed firms will help determine the valuation gains for cross-listed firms from emerging markets, as previous research work has not explored this dimension.

There is extensive literature that has analysed the effect of market risk on firms' stock returns, focusing on both developed and emerging economies (see Abbas et al., 2013; Ahmad et al., 2013; Asgharian et al., 2015; Baker et al., 2016; Balli et al. 2021; Chuliá et al., 2017; Dinga et al., 2021; Ludvigson, Ma, & Ng, 2018; Mensi et al., 2016, 2017; Ozturk & Pan et al., 2017; Phan et al., 2018; Sheng, 2018; Sua et al. 2019). These studies focused on the linear and non-linear correlation of the firm's stock return to market risk. However, none of these studies focused on conducting impact analysis for cross-listed firms.

Previous empirical investigations on the impact of conditional structural breaks on financial markets and stock returns have focused on the spillover effect of the global financial crisis from the U.S. financial market on the emerging economies markets (Chuliá et al., 2017; Hammoudeh et al., 2016; Mensi et al., 2016, 2017). However, firms from emerging markets cross-list on developed economies' stock markets and are therefore exposed to risk both in the cross-listed and their home markets, as reflected in the spillover effect of volatility in U.S. and emerging markets. There is the need to analyse the likely impact of these structural breaks on cross-listed firms' performance in this context, as this will enable us to assess the potential gain of cross-listing when firms are compared to their domestic peers. However, for this research work, the focus will be on the impact of structural breaks on firms' financial performance in the listed foreign market. In view of the above analysis the hypothesis has been formulated.

> ***H_{01}:** Cross-listed firms have a negative asymmetry risk exposure on stock returns due to economic policy uncertainty.*

Methodology

We examine firms from the emerging economies group (EEG) (i.e., Argentina, Brazil, China, India, Indonesia, Republic of Korea, Malaysia, Mexico, Russia, Saudi Arabia, South Africa, and Turkey) that are cross-listed and their stock returns on the London Stock Exchange (LSE). Daily firm stock price data were obtained from the Bloomberg database. In addition, the log returns of the firm's stock index prices were used for analyses. Bloomberg industry classification wasadopted for the study. Any firm that did not fall into the Bloomberg major industry classifications were excluded from the sample for analysis. Also, firms that have less than three years of observation were dropped. Given this position, the sample size consists of 4224 observations of daily stock returns for 84 firms from 8 out of the 12 EEG countries identified this was converted to monthly stock return with 252 observations. The following countries were left out of the analysis due to the non-availability of data, i.e., Argentina, Indonesia, the Republic of Korea, and Saudi Arabia. The breakdown of firms analysed from each identified country are as follows: Mexico 1; Russia 8; South Africa 14, China 35; Malaysia 16; India 8; Brazil 1, Turkey 1.

The www.policyuncertainty.com website served as the source for the uncertainty index that was used. These is consistent with the works of Chuliá et al., 2017, and Balli et al., 2021 who used similar data from the website in deriving their data set. The EPU was constructed by Ahir, Bloom and Furceri (2018) using quarterly indices of economic uncertainty derived from 143 countries using data on major political and economic development obtained from the Economist Intelligence Unit (EIU). Their analysis used major economic distortions such as the Gulf War II, US 9/11 attack, SARS outbreak, Euro debt crisis, Europe border-control crisis, Brexit referendum, and the presidential election in the U.S. in 2016 in constructing the index. It is noted that the index is correlated to EPU, EMU and GDP growth rate. Baker et al., (2016) developed the EPU index. Our data set sampling period is from the year 2000 to the year 2020.

Model Specification

The dynamic conditional correlational generalised autoregressive conditional heteroskedasticity (DCC-GARCH) framework was used to forecast the volatility of firm's stocks return on the London stock exchange. This model was developed by Engel (2001). It is a GARCH model which allows the researcher to address the issue of difference in frequencies of the dataset by giving the researcher the ability to combine firms stock daily return to the EPU monthly data for analysis. To address the issue of mixed data set in our sample (data on EPU is presented monthly while data on stock returns is presented daily), we use the pivotal table in excel to convert daily stock returns to monthly stock returns. This was done to address rebalancing bias, i.e., a stock index price moving between a stationary bid-ask price due to trading not taking place on a particular stock, as observed from the data downloaded. This is meant not to give a false test result on the firm's abnormal return (A.R.) (see Fama, 1998; Mitchell & Stafford, 2000). After that, apply the dynamic conditional correlation generalised autoregressive conditional heteroskedasticity (DCC GARCH) model. This will enable us to examine the covariance matrix of cross-listed firms' stock returns and EPU while also measuring the spillover effect of EPU. The variability in the model is expressed as:

$$\sigma_t^2 = \alpha_0 + \Sigma_{i=1}^{q} \alpha_1 \varepsilon_{t-1}^2 \tag{1}$$

α_0 is the mean, α_1 represent the conditional volatility while $\varepsilon_{t-1}$is the time series data's error term.

The GARCH model is used to synchronise the lagged squared errors and lagged variance in the model, which addresses the restrictions of the ARCH model's use with reference to the volatility clustering. This will ensure that the GARCH model is dependent on both present and past variance simultaneously to achieve volatility clustering. The GARCH (p, q) is therefore specified as follows:

$$. \sigma_t^2 = \omega + \Sigma_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 + \Sigma_{i=1}^{p} \beta_i \sigma_{t-j}^2 \tag{2}$$

The firm's stock return $R_{i,t}$ at day i = 1, 2, ..., p, while $\omega, \alpha_j, \beta_i$ denotes our conditional volatility with a non-negative constant $\alpha_j + \beta_i < 1$. ε_{t-j} is the error term and the lagged value for the conditional volatility. The ARCH component of our model is $\alpha_j and \varepsilon_{t-j}^2$ while $\beta_i and \sigma_{t-j}^2$ depicts the GARCH components. It should be noted that both the ARCH and GARCH model depend on the assumption that the shock effect on stock volatility has a symmetric distribution.

Results and Discussion

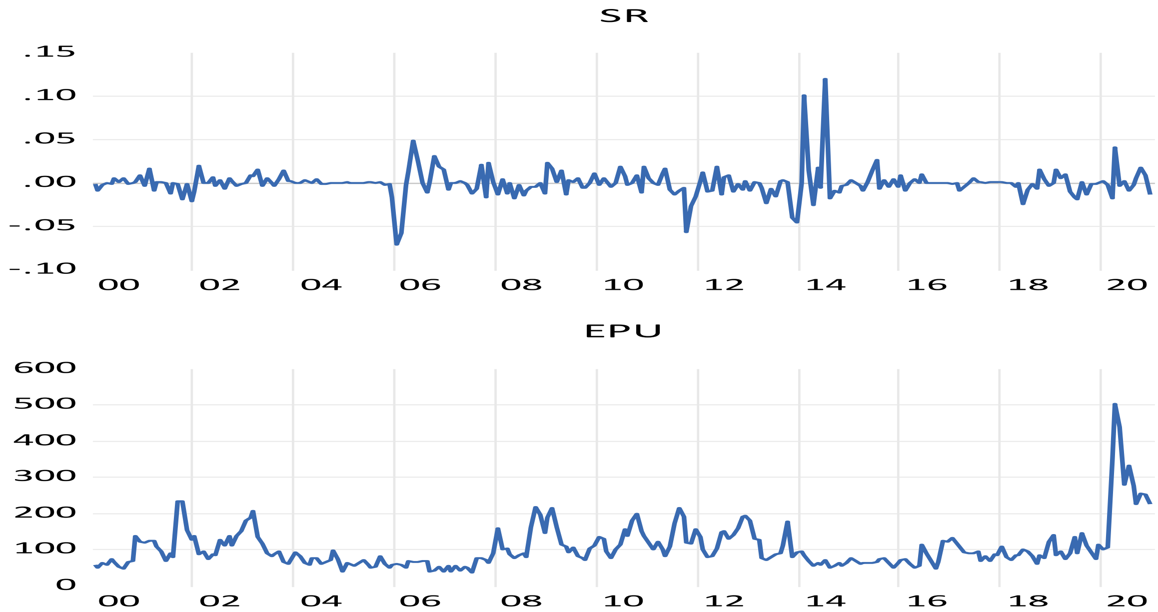
The analysis begins with the application of the Box-Jenkins method to determine the presence of volatility patterns in the investigated firms' stock returns. This method is used to estimate the ARCH and GARCH models.The Augmented Dickey-Fuller (ADF) test is then used to conduct a stationarity test. Table 1 presents the summary of daily observations of stock returns from cross-listed firms on the London Stock Exchange from the emerging economic group of countries and the economic policy uncertainty monthly data downloaded from www.policyuncertainty.com.

Table 1

	SR	**EPU**
Mean	-0.000546	104.4570
Median	0.000000	86.65289
Maximum	0.119292	503.0123
Minimum	-0.071393	37.26599
Std. Dev.	0.016086	61.35386
Skewness	1.985796	2.719118
Kurtosis	22.63680	14.04921
Jarque-Bera	4214.463	1592.424
Probability	0.000000	0.000000
Sum	-0.137562	26323.16
Sum Sq. Dev.	0.064951	944838.4
Observations	252	252

The standard deviation for stock return is 0.0161 and 61.3539 for economic policy uncertainty (EPU). Also, the maximum value for stock return (EPU) is 0.1193 (503.0123), and the minimum value for stock return (EPU) is -0.0714(37.2660), which shows a significant gap. This reflects high volatility in stock returns and structural breaks. The skewness value for stock returns (EPU) is 1.986 (2.719), reflecting that stock returns and EPU for the analysed firms are positively skewed. These values are more significant than zero, the expected skewness value.
Furthermore, the kurtosis is leptokurtic with a value of 22.637 (14.049) for stock returns (EPU), respectively. This indicates that returns for cross-listed firms on the LSE are not normally distributed as they are sensitive to market volatility due to structural breaks. Therefore, the results obtained justified using the ARCH/GARCH model for our analysis since the data can be best described as not normally distributed, leptokurtic, and fat-tailed.

Figure 1 – Stock Return (S.R.) and Economic Policy Uncertainty (EPU)



A visual inspection of stock returns of cross-listed firms on the LSE from fig. 1 shows that the white noise criteria has been violated as it can be seen that the standard deviation for firm's stock returns are not constant over time as the picture depicts period of low and high volatility.

Table 2 – Augmented Dickey Fuller (ADF) Test

Null Hypothesis: S.R. has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-13.61940	0.0000
Test critical values:	1% level	-3.456302	
	5% level	-2.872857	
	10% level	-2.572875	

*MacKinnon (1996) one-sided p-values.

The ADF test results in P0.05 at the 1%, 5%, and 10% levels of significance in Table 2, indicating that the time series is stationary and therefore mean-revertingand thereby confirms that the model is devoid of autocorrelation. Given the stationarity of the series, we take the next step of determining the best-fit mean equation by applying the ARMA DCC-GARCH model, which is presented in the table below:

Table 3 – DCC GARCH Output

Dependent Variable: S.R.
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 05/19/22 Time: 23:20
Sample: 2000M01 2020M12
Included observations: 252
Convergence achieved after 15 iterations
Coefficient covariance computed using QML sandwich with observed Hessian
Presample variance: unconditional
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.001207	0.000594	2.031984	0.0422
Variance Equation				
C	8.26E-06	1.07E-05	0.771821	0.4402
RESID(-1)^2	0.700854	0.374034	1.873769	0.0610
GARCH(-1)	0.570085	0.083425	6.833542	0.0000

R-squared	-0.011924	Mean dependent var	-0.000546
Adjusted R-squared	-0.011924	S.D. dependent var	0.016086
S.E. of regression	0.016182	Akaike info criterion	-5.933878
Sum squared resid	0.065725	Schwarz criterion	-5.877855
Log likelihood	751.6686	Hannan-Quinn criter.	-5.911336
Durbin-Watson stat	1.688244		

Table 4 - EPU

Dependent Variable: EPU
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 05/19/22 Time: 23:18
Sample: 2000M01 2020M12
Included observations: 252
Convergence achieved after 24 iterations
Coefficient covariance computed using QML sandwich with observed Hessian
Presample variance: unconditional
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	83.65831	15.01925	5.570074	0.0000
Variance Equation				
C	1073.926	807.1720	1.330480	0.1834
RESID(-1)^2	0.818520	0.395514	2.069508	0.0385
GARCH(-1)	-0.127515	0.211099	-0.604053	0.5458

R-squared	-0.115376	Mean dependent var	104.4570
Adjusted R-squared	-0.115376	S.D. dependent var	61.35386
S.E. of regression	64.79664	Akaike info criterion	10.37366
Sum squared resid	1053850.	Schwarz criterion	10.42969
Log likelihood	-1303.082	Hannan-Quinn criter.	10.39621
Durbin-Watson stat	0.293687		

Table 3 & 4 shows the univariate output for S.R. (EPU) with their ARCH value (i.e., RESID(-1)^2)). This value is positive and not statistically significant for S.R. but significant for EPU. The GARCH coefficient (GARCH(-1)) is positive and significant for S.R. while negative and not significant for EPU, indicating strong evidence of volatility clustering for S.R. To get a clearer view, we carried out a DCC analysis to observe the level of volatility clustering.

Table 5

System: 2-Step DCC(1,1) model with univariate GARCH fitted in the 1st step
Estimation Method: ARCH Maximum Likelihood (BFGS) - Two Step
Covariance specification: Dynamic Conditional Correlation with correlation targeting
Date: 05/19/22 Time: 19:59
Sample: 2000M01 2020M12
Included observations: 252
Total system (balanced) observations 504
Bollerslev-Wooldridge robust
standard errors & covariance
for univariate fits
Disturbance assumption: Multivariate Normal distribution
Presample covariance: Unconditional
Failure to improve objective (non-zero gradients) after 18 iterations
Hessian

	Coefficient	Std. Error	z-Statistic	Prob.
theta(1)	-0.017656	NA	NA	NA
theta(2)	0.782187	NA	NA	NA
C(9)	-0.112021	0.113422	-0.987647	0.3233
	-283.5410			2.491689

Log likelihood	-0.562581	Schwarz criterion	2.399618
Avg. log likelihood	2.337627	Hannan-Quinn criter.	4.474065
Akaike info criterion	4.423344		

* Stability condition: theta(1) +
theta(2) < 1 is met.

From table 5above, the stability condition shows that theta(1) + theta(2) were met; hence the application of the DCC GARCH model is appropriate. The results obtained revealed a coefficient value of -0.017656 (0.782187), reflecting both positive and negative correlations for S.R. This reflects that cross-listed firms from EEG economies experience negative returns due to structural breaks caused by the EPU and the spillover effect of the U.S. stock market.

Conclusion and Recommendations

From the analysis above the paper provides evidence to support that economic policy uncertainty is a significant source of a structural break with a negative impact on the aggregate performance of firms from the emerging economic group of countries. Therefore, it is imperative that firms from the emerging economic group of countries consider the stability and volatility in their proposed listing market before deciding to list in a foreign market. Future research can also be carried out by carrying out a comparative analysis using constant conditional correlation GARCH (CCC-GARCH), varying conditional correlation GARCH (VCC-GARCH) and comparing it to the results of the DCC-GARCH as these three models are used for multivariate GARCH analysis.

References

Ahir, Bloom & Furceri (2018). The World Uncertainty Index. Mimeo.

Ahmad, W., Sehgal, S., &Bhanumurthy, N. R. (2013). Eurozone crisis and BRICKS stock markets: Contagion or market interdependence? *Economic Modelling*, 33, 209 – 225.

Andrikopoulos, A., Chen, Z., Chortareas, G., & Li, K. (2023). Global economic policy uncertainty, gross capital inflows, and the mitigating role of macroprudential policies. *Journal of International Money and Finance*,131, 1 – 26.

Asgharian, H., Christiansen, C., & Hou, A.J. (2015). Effects of macroeconomic uncertainty on the stock and bond markets. *Finance Research Letters*, 13, 10 – 16.

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *Quarterly Journal of Economics*, 131(4), 1593 – 1636.

Bali, T.G., Brown, S.J., & Tang, Y. (2014). Macroeconomic Uncertainty and Expected Stock Returns. Working Paper SSRN.

Balli, F., Hasan, M., Ozer-Balli, H., & Gregory-Allen, R. (2021). Why do U.S. uncertainties drive stock market spill overs? International evidence. *International Review of Economics & Finance*, 76, 288 – 301.

Bekaert, G., Ehrmann, M., Fratzscher, M. & Mehl, A. (2014). The Global Crisis and Equity Market Contagion. *Journal of Finance*, 69(6), 2597 – 2649.

Benos, E.; Weisbach, M. (2004). Private Benefits and Cross-Listings in the United States. *Emerging Markets Review* 5, 217–240.

Berk, J., DeMarzo, P., Harford, J., Ford, G., Mollica, V., & Finch, N. (2015). *Fundamentals of Corporate Finance (2nd ed.)*. Pearson Australia Group Pty Ltd.

Bollerslev, T. (1986). Generalised autoregressive conditional heteroscedasticity. *Journal of Econometrics*, 31, 307 – 327.

Carrière-Swallow, Y. and Céspedes, L.P. (2013). The impact of uncertainty shocks in emerging economies.*Journal of International Economics*, 90(2), 316 – 325.

Cetorelli, N and Peristiani, S. (2015). Firm Value and Cross Listings: The Impact of Stock Market Prestige. *Journal of Risk and Financial Management*, 8, 150 – 180.

Chiang, S. M., Chen, H. F., & Lin, C. T. (2013). The spillover effects of the sub-prime mortgage crisis and optimum asset allocation in the BRICV stock markets. *Global Finance Journal*, 24, 30 – 43.

Chuliá, H., Gupta, R., Uribe, J.M., &Wohar, M.E. (2017). Impact of U.S. uncertainties on emerging and mature markets: Evidence from a quantile-vector autoregressive approach. *Journal of International Financial Markets, Institutions & Money*, 48, 178 – 191.

Conrad, C., & Loch, K. (2015). Anticipating long-term stock market volatility. *Journal of Applied Econometrics*, 30, 1090 – 1114.

Dinga, W., Levine, R., Lina, C., &Xie, W. (2021). Corporate immunity to the COVID-19 pandemic. *Journal of Financial Economics,* 141, 802 – 830.

Drechsler, I. (2013). Uncertainty, time-varying fear, and asset prices. *The Journal of Finance*, 68, 1843 –1889.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica*,50, 987 – 1007.

Engle, R., Ghysels, E., & Sohn, B. (2013). On the economic sources of stock market volatility. *Review of Economics and Statistics,* 93, 776 – 797.

Engle, R.F., Lilien, D.M., & Robins, R.P. (1987). Estimating time varying risk premia in the term structure: The ARCH-M model. *Econometrica*, 55, 391 – 407.

Errunza, V.R. & Miller, D.P. (2000). Market Segmentation and the Cost of Capital in International Equity Markets. *The Journal of Financial and Quantitative Analysis,* 35(4), 577 – 600.

Gaspars-Wieloch, H. (2019). Project net present value estimation under uncertainty. *Central European Journal of Operations Research.* 27, 179 – 197.

Gauvin, L., McLoughlin, C., & Reinhardt, D. (2014). Policy uncertainty spillovers to emerging markets – evidence from capital flows. *Bank of England. Quarterly Bulletin,* 54(4), 457.

Ghysels, E., Santa-Clara, P. &Valkanov, R. (2005). There is a risk-return trade-off after all. *Journal of Financial Economics*, 76, 509 – 548.

Ghysels, E., Santa-Clara, P., &Valkanov, R. (2006). Predicting volatility: getting the most out of return data sampled at different frequencies. *Journal of Econometrics*, 131, 59 – 95.

Hammoudeh, S., Kang, S.H., Mensi, W., & Nguyen, D.K. (2016). Dynamic Global Linkages of the BRICS Stock Markets with the United States and Europe Under External Crisis Shocks: Implications for Portfolio Risk Forecasting. *The World Economy*, 1703 – 1727. https://doi.org/10.111/twec.12433

Hwang, E., Min, H. G., Kim, B. H., & Kim, H. (2013). Determinants of stock market co-movements among U.S. and emerging economies during the U.S. financial crisis. *Economic Modelling*, 35, 338 – 348.

Julio, B., &Yook, Y. (2016). Policy uncertainty, irreversibility, and cross-border flows of capital. *Journal of International Economics, 103,* 13-26.

Karolyi, A. (2006). The world of cross-listings and cross-listings of the world: Challenging conventional wisdom. *Review of Finance*, 10, 1–54.

Ludvigson, S. C., Ma, S., & Ng, S. (2018). Uncertainty and business cycles: Exogenous impulse or endogenous response? NBER Working Paper, No, 21803.

Mensi, W., Hammoudeh, S., Nguyen, D.K., & Kang, S.H. (2016). Global financial crisis and spillover effects among the U.S. and BRICS stock markets. *International Review of Economics & Finance*, 257 – 276.

Mensi, W., Hammoudeh, S., Nguyen, D.K., & Kang, S.H. (2017). Dynamic linkages between developed and BRICS stock markets: Portfolio risk analysis. *Finance Research Letters,* 21, 26 – 33.

Mensi, W., Hammoudeh, S., Reboredo, J.C., & Nguyen, D.K. (2014). Do global factors impact BRICS stock markets? A quantile regression approach. *Emerging Markets Review*, 19, 1 – 17.

Narayan, P.K., Phan, D.H.B., Narayan, S., &Bannigidadmath, D., (2017). Is there a financial news risk premium in Islamic stocks? *Pacific-Basin Finance Journal,* 42, 158 – 170.

Ozturk, E. O., & Sheng, X. S. (2018). Measuring global and country-specific uncertainty. *Journal of International Money and Finance*, 88, 276 – 295.

Pan, Z., Wang, Y., Wu, C., & Yin, L. (2017). Oil price volatility and macroeconomic fundamentals: A regime switching GARCH-MIDAS model. *Journal of Empirical Finance*, 43, 130–142.

Pagano, M.; Röell, A.; Zechner, J. (2002). The Geography of Equity Listing: Why Do Companies ListAbroad? *Journal of Finance*, 57, 2651–2694.

Phan, D.H.B., Sharma, S.S., & Tran, V.T. (2018). Can economic policy uncertainty predict stock returns? Global evidence. *Journal of International Financial Market, Institution & Money*, 55, 134 – 150.

Su, Z., Fang, T., & Yin, L. (2017). The role of news-based implied volatility among U.S. financial markets. *Economics Letters*, 157, 24 – 27.

Su, Z., Fang, T., & Yin, L. (2019). Understanding stock market volatility: What is the role of U.S. uncertainty? *The North American Journal of Economics and Finance*, 48, 582 – 590.

Ying, Q., Kong, D., & Luo, D. (2015). Investor attention, institutional ownership, & stock return: Empirical evidence from China. *Emerging Markets Finance and Trade,* 51, 672 – 685.

Zhang, B., Li, X., Yu, H. (2013). Has recent financial crisis changed permanently the correlations between BRICS and developed stock markets? *North America Journal of Economics & Finance*, 26, 725 –738.