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Susceptibility of Stock Market Returns to International Economic Policy: Evidence from Effective Transfer Entropy of Africa with the Implication for Open Innovation

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Abstract: This study contributes to the scant finance literature on information flow from international economic policy uncertainty to emerging stock markets in Africa, using daily US economic policy uncertainty as a proxy and the daily stock market index for Botswana, Egypt, Ghana, Kenya, Morocco, Nigeria, Namibia, South Africa, and Zambia from 31 December 2010 to 27 May 2020, using the Rényi effective transfer entropy. International economic policy uncertainty transmits significant information to Egypt, Ghana, Morocco, Namibia, and South Africa, and insignificant information to Botswana, Kenya, Nigeria, and Zambia. The asymmetry in the information transfer tends to make the African market an alternative for the diversification of international portfolios when the uncertainty of the global economic policy is on the rise. The findings also have implications for the adoption of open innovation in African stock markets.

Keywords: economic policy uncertainty; Rényi transfer entropy; effective transfer entropy; African stock markets

1. Introduction

The response of financial markets to the global financial crisis of 2008/2009 (GFC) and the current coronavirus disease 2019 (COVID-19) pandemic echoed the impact of globalization on the financial market of developed and emerging markets. Economic and financial disturbance from one country, especially from the world's leading economies, significantly impacts developing countries [1–3]. A typical example is the recent economic downturn and the US economic recession, which spread from the US housing market to the US financial market, leading to the global financial crisis. This reemphasizes the adage that "when America sneezes, the whole world catches a cold". What, then, happens to Africa when America catches a cold? It is, therefore, unsurprising that studies on the impact of US economic policy uncertainty on different financial markets are flourishing in empirical finance literature. Policy instability or uncertainty could delay decision-making and adversely affect economies and price reactions in financial markets [4–7]. As noted by Carrière-Swallow and Céspedes [8], there is substantial heterogeneity in reactions to these shocks across countries, and emerging economies suffer more and take longer to recover. The reaction of African stock markets and the inability of most markets to return to pre-GFC is a confirmation of the difficulty in overshoot activities following uncertainty [8,9].

Similarly, preliminary analyses by various agencies and organizations of the likely impact of global economic uncertainty stemming from the coronavirus disease 2019 (COVID-19) pandemic on Africa's economic agents point to a disastrous consequence. The Organization of Economic Cooperation and Development (OECD) [10] expressed concern about the likely disastrous impact of COVID-19 on Africa due to the reduction of trade and investment from China in the immediate term, as well as a fall in global demand and a disruption in the supply chain, leading to a slowdown in trade. The United Nations Commission on Africa (UNCA) [11] predicts a slowdown of growth to 1.8% and the potential to push about 27 million people into extreme poverty. All these are an indication of the vulnerability and susceptibility of African economies to global economic uncertainty. However, there is little documented evidence regarding how US economic policy uncertainty interacts with economic agents such as stock markets in Africa. The current study examines the information flow from US economic policy uncertainty to returns of African stock markets. This is the premise of both the efficient market hypothesis (EMH) and the macroeconomic expectations hypothesis (MEH). The EMH holds that stock prices correctly reflect information available at that time of pricing [12]. This implies that information that suggests future economic activity is a key conditioning factor in determining the current prices of financial assets and, hence, returns. In support of EMH, the MEH suggests that stock markets are forward-looking in nature, and hence, asset returns reflect economic information [13]. In this regard, depending on the information the market picks up from global economic policy uncertainty, stock prices may be positively or negatively influenced. The introduction of the formal construct for the measurement of the economic policy uncertainty index (EPU) by Baker et al. [14] has heightened the economic policy uncertainty and stock market performance nexus. For example, using Baker et al. [14] to measure EPU, several research studies have recorded a negative relationship between the stock market and EPU [4,5,15–17]. The focus of these studies has generally been on the relationship between stock markets and domestic EPU. Notwithstanding, there is evidence of an international economic policy uncertainty spillover. In particular, US EPU shocks have been found to negatively and significantly affect stock market returns in Brazil, Canada, China, India, Japan, Korea, and Russia [3,18].

The consequences of the global financial crisis have shown that global systemic risk is more pervasive and far-reaching. Hence, this study focuses on the relationship between international EPU (specifically the US EPU) and African stock returns, something which is conspicuously missing from the existing literature.

African stock markets have long been seen as prime candidates for inclusion in the portfolio of international investors seeking international diversification [9,19]. However, the emergence of Africa as a destination for foreign investment from across the globe is gradually integrating African stock markets into the world, making them susceptible to global uncertainty [9,19,20]. In particular, African stocks, for example, recorded the sharpest decline relative to other regional markets in their returns during the 2008/2009 financial crisis [9]. The ability of African stock markets to respond to global pressures such as economic policy uncertainty depends on adaptive capabilities and innovativeness. However, closed innovation, which increases the asymmetry of information, is criticized by the literature as having been directly responsible for the financial crisis of 2008/2009 [21,22]. The notion of uncertainty is viewed as equivalent to that of incomplete information to make an informed decision. Innovation strategies for the African stock markets must factor internal and external ideas in the form of open innovation to better deal with global uncertainty. It is, therefore, appropriate to investigate how African stock markets respond to global economic uncertainty to inform policymakers and international investors.

This article contributes to the literature by first employing transfer entropy to quantify and test information flow from international EPU to African stock markets for the first time. Using transfer entropy widens the possibilities to detect information flows, as nonlinear relationships can also be accounted for. Specifically, Rényi transfer entropy, which allows one to focus on specific parts of a distribution, such as center or tail observations, e.g., financial return data, generally exhibits fat-tailed nonnormal empirical distributions. This feature is of special interest in finance and renders Rényi transfer entropy a most appealing tool to analyze information flows between financial time series.

The rest of the paper is structured as follows: The next section discusses the methodology, and the third section presents the data, results, and discussions, while the final section presents the conclusions.

2. Literature Review and Methodology

2.1. Literature Review

The interest in the effect of economic policy uncertainty on various economic agents has increased due to recent events that have brought about uncertainty in the economic environment, such as the US subprime-induced global financial crises, the European sovereign debt crisis, Brexit, US–China trade tension, and the recent COVID-19 pandemic. Baker et al. [14] refer to economic policy uncertainty as a nonzero probability of change in existing economic policies that determine the rules of the game for economic agents. Policy uncertainty may affect a firm's decision-making regarding investment, consumption, savings, and supply channels, among others [21,23–25]. Furthermore, it affects inflation, interest, expected risk premium, and level of value of protection provided by the government, which may lead to an increase in risk in financial markets [4,26]. Thus, economic policy uncertainty tends to influence stock returns, depending on the information picked as espoused in an efficient market and on macroeconomic expectation hypotheses. Recent studies have confirmed the sensitivity of stock returns to economic policy uncertainty [15–17,25,27].

The issue of whether the sensitivity of equity markets to economic policy uncertainty is local or global remains to be investigated. The relationship between a country's economic activity and global economic activity has been found to dictate expected returns [28–30]. Bartman et al. [31], however, argue that firms in different countries may have different levels of idiosyncratic risk, implying that some countries have different strengths in their exposure to systematic factors. This was corroborated by Mehl [32] who examined the sensitivity of equity returns to global factors and observed that exposure depends on the openness of the local economy. Das and Kumar [33] employed multiple and partial wavelets to examine the interdependence of international economic policy uncertainty with the returns of 11 developed and 6 emerging market equities. The emerging economies were found to be less vulnerable to international economic policy uncertainty proxied by US economic policy uncertainty compared to the developed markets. The extent of interdependency and risk exposure varied across countries. The possibility of the heterogeneity of risk exposure depends on the level of integration of the economy into the global economy. Though African markets are not completely disconnected from the global economy, they are yet to completely catch up with global stock markets [19]. Adam and Gyamfi [19] employed the integration factor from the international capital asset pricing model to study the time-varying integration of African stocks to global equity markets and observed an emerging trajectory to integration. In spite of evidence of an incomplete integration of African stock markets, spillovers from global markets severely affect African markets as noted by Sugimoto et al. [34] using the Diebold and Yilmaz [35] index. At the country level, Cakan and Gupta [36] showed that while bad news about US inflation does not affect the volatility of South African stock returns, good news tends to increase volatility. Similarly, Belcaid and El Ghini [37] showed that volatility in the Moroccan stock market is to explain economic policy uncertainty in France, Spain, and the US. What is missing is how African stock returns respond to broader economic uncertainty measured via economic policy uncertainty.

From a methodological viewpoint, previous studies approached the interaction of African stock markets with global economic activities using both linear and nonlinear models of independence and causal relationships. Such methods are unable to quantify the amount of information flow from global economic activities to African stock markets. To overcome such limitations, the concept of transfer entropy was proposed by Schreiber [38] to measure the amount of information flow. Transfer entropy is a nonparametric measure of the amount of information transfer from a variable to a variable based on the Shannon entropy [39]. Marschinski and Kantz [40] proposed an effective transfer entropy to obtain a more robust quantification of information flow to minimize the weakness of transfer entropy, which is evolving noise due to its requirement of a large amount of data. Effective transfer entropy has been used widely in the literature to identify information flows in different financial markets [41–45].

2.2. Methodology

Measuring Information Flows Using Rényi Transfer Entropy

According to Behrendt et al. [46], transfer entropy is rooted in information theory and based on the concept of the Shannon entropy as a measure of uncertainty. Consider a discrete random variable J with probability distribution $p(j)$, where j denotes possible outcomes or (in terms of information theory, see Dimpfl and Peter [47]) possible symbols of J. Hartley [48] defined the average information per symbol as $\mathrm{H} = \sum_{j=1}^{n} P_j log_2\left(\frac{1}{P_j}\right)$ bits, where n is the number of distinct symbols associated with the probabilities P_j. It follows that Shannon [36] entropy of $p(j)$ is given by

$$\mathrm{H}J = -\sum\nolimits_j P(j) log_2 P(j). \tag{1}$$

Shannon's formula measures the uncertainty which increases with the number of bits needed to optimally encode a sequence of realizations of J. The Shannon entropy together with the Kullback–Leibler distance under the Markov processes assumption enables information to flow between two time series. For two discrete random variables I and J, the marginal probability distributions are $p(i)$ and $p(j)$ and the joint probability is $p(i, j)$, whose dynamical structures correspond to a stationary Markov process of order k (process I) and l (process J). The Markov property implies that the probability to observe I at time $t + 1$ in state i conditional on the k previous observations is $p(i_{t+1}|i_t, \ldots, i_{t-k+1}) = p(i_{t+1}|i_t, \ldots, i_{t-k})$. The average number of bits desired to encode the observation in $t + 1$, once the previous k values are known, is given by

$$h_j\ (k) = -\sum\nolimits_i P\left(i_{t+1}, i_t^{(k)}\right) log P(i_{t+1}|i_t^{(k)}), \tag{2}$$

where $i_t^{(k)} = (\mathrm{i}_t, \ldots, \mathrm{i}_{t-k+1})$ (analogously for process J). In the case of bivariate, the information flow from process J to process I is measured by quantifying the deviation from the generalized Markov property $p(i_{t+1}\ |i_t^{(k)}) = p(i_{t+1}|\ i_t^{(k)}, j_t^{(i)})$, relying on the Kullback–Leibler distance. The formula for the Shannon transfer entropy is given by

$$T_{\mathrm{J}\rightarrow\mathrm{I}}\ (\mathrm{k},\ 1) = \sum p\left(i_{t+1},\ i_t^{(k)},\ j_t^{(I)}\right) log\ \frac{P(i_{t+1}|\ i_t^{(k)}, j_t^{(I)}}{P(i_{t+1}|\ i_t^{(k)}}, \tag{3}$$

where $\mathrm{T}_{J\rightarrow I}$ measures the information flow from J to I. $\mathrm{T}_{I\rightarrow J}$, as a measure for the information flow from I to J, can be derived analogously. The dominant direction of the information flow can be inferred by calculating the difference between $\mathrm{T}_{J\rightarrow I}$ and $\mathrm{T}_{I\rightarrow J}$.

Jizba et al. [49] proposed that transfer entropy can also be based on the Rényi entropy rather than the Shannon entropy as introduced by Rényi [50]. The Rényi entropy depends on a weighting parameter q and can be calculated as

$$H_J^q = \frac{1}{1-q} log \sum\nolimits_j P^q(j), \tag{4}$$

with $q > 0$. For $q \rightarrow 1$, the Rényi entropy converges to the Shannon entropy. For $0 < q < 1$, an event that has a low probability receives more weights, while for $q > 1$ the weights favor outcomes j with a higher initial probability. Consequently, the Rényi entropy allows emphasizing different areas of distribution, depending on the parameter q [46].

Using the escort distribution [51], $\phi q(j) = \frac{P^q(j)}{\sum_j P^q(j)}$ with $q > 0$ to j normalize the weighted distributions, Jizba et al. [49] derive the Rényi transfer entropy as

$$RT_{\mathrm{J}\to\mathrm{I}}(K, I) = \frac{1}{1-q} log \frac{\sum_i \phi_q\left(i_t^{(k)}\right) P^q\left(i_{t+1} | \, i_t^{(k)}\right)}{\sum_{i,j} \phi_q\left(i_t^{(k)}, j_t^{(l)}\right) P^q\left(i_{t+1} | \, i_t^{(k)}, j_t^{(l)}\right)}. \tag{5}$$

Note that the calculation of the Rényi transfer entropy can result in negative values. In such a situation, knowing the history of J reveals even greater uncertainty than would otherwise be indicated by only knowing the history of I alone.

As noted by Marschinski and Kantz [39], the transfer entropy estimates are biased in small samples. The correction of the bias is possible and can be used to calculate the effective transfer entropy as

$$ETE_{\mathrm{J}\to\mathrm{I}}(\mathrm{k},\, \mathrm{l}) = T_{\mathrm{J}\to\mathrm{I}}(\mathrm{k},\, \mathrm{l}) - T_{Jshuffled\to\mathrm{I}}(\mathrm{k},\, \mathrm{l}), \tag{6}$$

where $T_{Jshuffled\to\mathrm{I}}(\mathrm{k},\, \mathrm{l})$ indicates the transfer entropy using a shuffled version of the time series J; that is randomly drawing values from the observed time series J and realigning them to generate a new time series, which destroys the time series dependencies of J as well as the statistical dependencies between J and I. This causes $T_{Jshuffled\to\mathrm{I}}(\mathrm{k},\, \mathrm{l})$ to converge to zero with an increasing sample size, and any nonzero value of $T_{Jshuffled\to\mathrm{I}}(\mathrm{k},\, \mathrm{l})$ is due to small sample effects. Thus, repeated shuffling and the average of the resulting shuffled transfer entropy estimates across all replications serve as an estimator for the small sample bias and subtracted from the Shannon or Rényi transfer entropy estimate to obtain a bias-corrected effective transfer entropy estimate.

Relying on a Markov block bootstrap, the statistical significance of the transfer entropy estimates, as given by Equation (7), can be assessed [46,47]. This preserves the dependencies within the variables J and I, but eliminates the statistical dependencies between them contrary to shuffling. Repeated estimation of transfer entropy then provides the distribution of the estimates under the null hypothesis of no information flow. The associated p-value is given by $1 - \hat{q}_T$, where $\hat{q}_T$ denotes the quantile of the simulated distribution that is determined by the respective transfer entropy estimate.

3. Data and Results

The data set for this analysis consists of the daily US economic policy uncertainty index (EPU) and daily stock market indexes for nine African countries, namely, Nigeria Stock Exchange All Share Index (Nigeria), Nairobi All Share Index (Kenya), Zambia All Share Index (Zambia), FT/JSE All Share Index (South Africa), Ghana Stock Exchange All Share Index (Ghana), Botswana Domestic Company Index (Botswana), Casablanca All Share Index (Morocco), Namibia Stock Exchange Overall Index (Namibia), and Egypt EGX30 (Egypt). The data ranges from 31 December 2010 to 27 May 2020, yielding 2389 observations. The EPU variable is an index constructed by Baker et al. [14] and is based on usage data from over 1000 newspapers from the Access World News Bank. The period of the study covers part of the global financial crisis from US subprime, European Sovereign debt crises, US–China trade tension, Brexit, and the emergence of COVID-19 as a global pandemic. The choice of the market was solely based on the availability of data, yet it contains most of the important markets in Africa. The analysis is based on the returns of daily stock indexes given as

$$r_t = lnP_t - lnP_{t-1}, \tag{7}$$

where r_t is the continuously compounded return, and P_t and P_{t-1} are the respective current and previous prices.

Figure 1 shows the time series plot of the nine African stock returns and the EPU of the US. We can see from the plots that the time series plots show stationarity and few volatilities interspersed with a stable period. We confirm the stationary properties with two different unit root tests: the augmented

Dickey–Fuller (ADF) and Phillips–Perron (PP) tests. Table 1 shows the summary statistics of the daily returns and unit root tests. All return series depart from normality. Notably, the average daily returns for all the nine stock indexes are negative and positive for the change in international EPU. Nonetheless, the average returns of all the stocks are close to zero. The standard deviations of all the nine returns are lower than that of the EPU change, with Botswana having the least. The risk-adjusted returns of all stocks are negative and positive for EPU. Additionally, the null hypothesis of no unit root in all the return series cannot be rejected from the augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests.

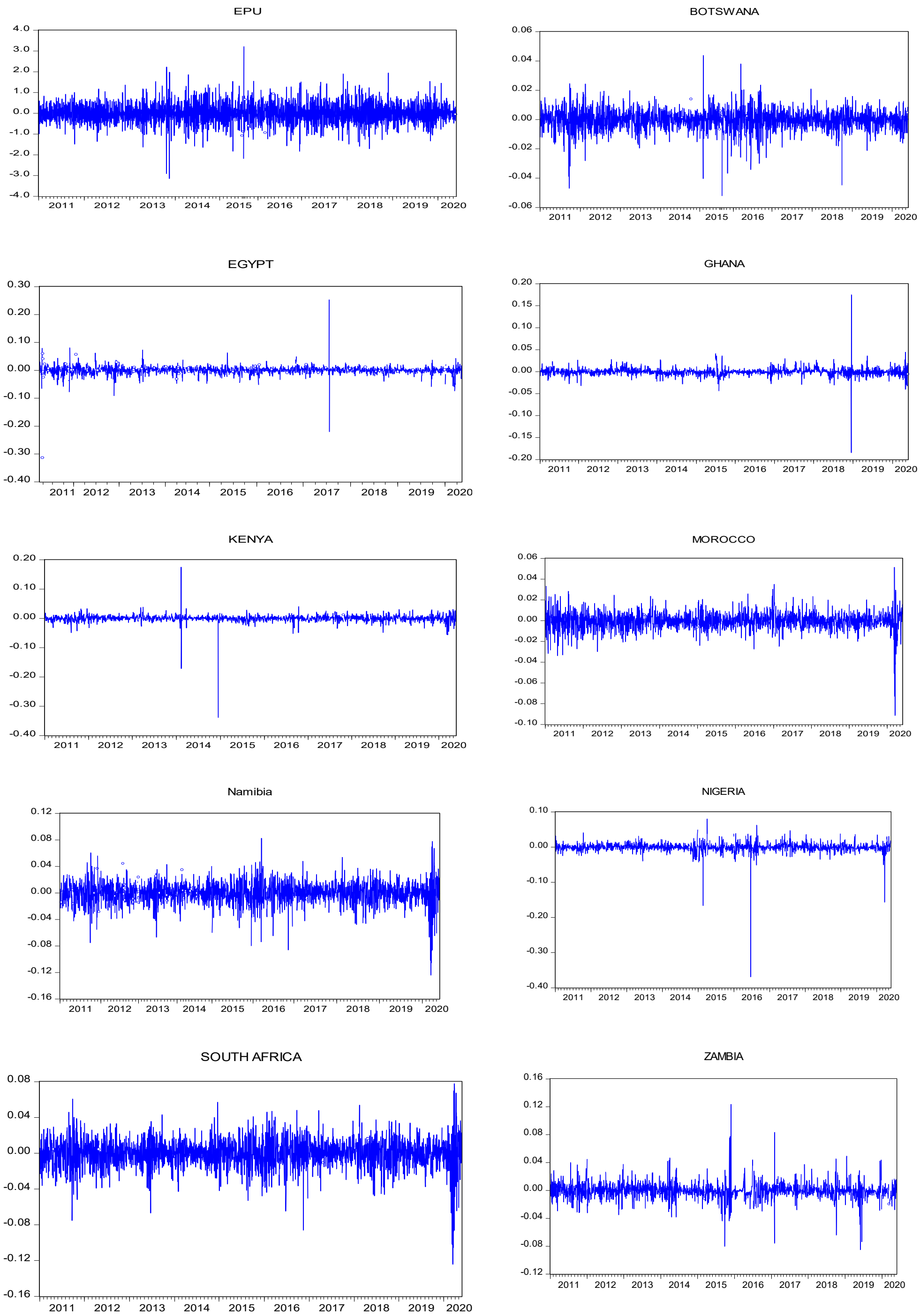

Figure 1. Time series plot of returns series and economic policy uncertainty index (EPU).

Table 1. Descriptive statistics and unit root test.

Countries	Mean	Std Dev.	Skewness	Kurtosis	Risk-Adjusted Mean	Jarque–Bera	ADF	PP
Botswana	−0.021	0.007	−0.650	9.061	−3.075	3618.274 ***	−48.886 ***	−48.915 ***
Egypt	−0.004	0.016	−2.889	106.553	−0.221	973,471.000 ***	−52.020 ***	−51.725 ***
Ghana	−0.029	0.009	−0.396	142.383	−3.178	186,511.000 ***	−11.999 ***	−54.455 ***
Kenya	−0.014	0.012	−8.895	274.502	−1.129	71,346.000 ***	−37.434 ***	−38.009 ***
Morocco	−0.019	0.008	−1.018	15.544	−2.367	15,295.590 ***	−42.238 ***	−42.238 ***
Namibia	−0.023	0.017	−0.693	7.939	−1.385	2421.507 ***	−44.861 ***	−44.861 ***
Nigeria	−0.034	0.014	−9.860	250.552	−2.507	5,858,732 ***	−40.348 ***	−40.404 ***
South Africa	−0.022	0.016	−0.671	7.735	−1.353	2362.746 ***	−49.001 ***	−49.050 ***
Zambia	−0.038	0.011	0.499	18.280	−3.361	22,088.790 ***	−42.054 ***	−42.013 ***
EPU	0.034	0.509	0.019	5.513	0.066	594.653 ***	−26.559 ***	−298.297 ***

Note: *** signifies significance at 10%, 5%, and 1% levels, respectively.

The computation of effective transfer entropy requires that the sample is recorded. The choice of the bins is motivated by the distribution of the data. Based on the density plot in Figure A1 in Appendix A, which is generated using the Epanechnikov kernel, three bins are proposed and divided the return data along with the 5% and 95% quantiles of the corresponding return distribution of the full data set. Given that $q^r_{[0.05]}$ and $q^r_{[0.95]}$ respectively denote 5% and 95% quantiles, the symbolic encoding replaces each value in the observed return time series, r_t, by a corresponding symbol (1, 2, 3). In this case, the intermediate bin is kept large to focus on extreme events, which enables us to isolate the effect of true information from the "normal" pattern of returns [41]. This is plausible in finance, pricing relevant information is readily associated with tail events, which refer to large positive and negative returns [46]. To quantify the weight of extreme uncertainty to information flow to stock returns, we estimate the effective transfer entropy for various weighting parameter q. The low values of q give information in the tails a larger weight.

$$S_t = \begin{cases} 1 & for\ r_t \leq q^r_{[0.05]} \\ 2 & for\ q^r_{[0.05]} < r_t < q^r_{[0.95]} \\ 3 & for\ r_t \geq q^r_{[0.95]} \end{cases}. \tag{8}$$

Table 2 presents the effective transfer entropy from international economic policy uncertainty to stock returns in Africa for various q values ($q = 0.1, 0.2, \ldots, 0.9$). The results show significant information flow from EPU to five out of the nine African Stock returns: Egypt, Ghana, Morocco, Namibia, and South Africa for all values of q. In all cases, there was no observed difference in the amount of information flow across different values of q, which is an indication that there is symmetry in the reaction of stock return to international policy uncertainty. The positive Rényi effective transfer entropy in all cases shows that the risk about the future returns of African stocks is reduced by the knowledge of the international economic policy uncertainty. A surprise increase in economic policy uncertainty poses a risk of exposure to African markets. In contrast to Adam and Gyamfi [19], an earlier observation of increased integration of African stock markets, especially Nigeria and Namibia, to the global financial markets showed that information flows from EPU to Botswana, Kenya, Nigeria, and Zambia were not significant at a 5% significance level at all levels of the parameter weighting. Figure 2 shows the heatmap of effective transfer entropy at the various parameter weighting. The results show that African stocks, like other emerging markets, are not completely insulated from international economic policy uncertainty. Similar findings of the asymmetric effect of international economic policy uncertainty on stocks of developing economies have been recorded [25,52,53]. Following the global financial crisis, financial markets have become more closely interconnected than ever [19] and global investors have become more sensitive to economic uncertainty, hence the flow of information from EPU across markets. The finding implies that EPU is relevant in predicting the return behavior of African stocks. The differences in the flow of information make African stocks candidates for both domestic and international diversification. This finding has significant implications for international investors and portfolio formation.

Table 2. Rényi effective transfer entropy from economic policy uncertainty to African stock returns.

EPU ↓↓	Parameter Weighting, *q*								
	0.1	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Botswana	0.0017	0.0017	0.0018	0.0018	0.0018	0.0016	0.0017	0.0017	0.0019
Egypt	0.0077 ***	0.0078 ***	0.0079 ***	0.0078 ***	0.0081 ***	0.0078 ***	0.0077 ***	0.0078 ***	0.0078 ***
Ghana	0.0065 ***	0.0064 ***	0.0063 ***	0.0064 ***	0.0062 ***	0.0062 ***	0.0064 ***	0.0064 **	0.0064 **
Kenya	0.0021 *	0.0023	0.0024	0.0024 *	0.0022	0.0023 *	0.0023 *	0.0024 *	0.002
Morocco	0.0088 ***	0.0084 ***	0.0085 ***	0.0082 ***	0.0082 ***	0.0083 ***	0.0081 ***	0.0087 ***	0.0085 ***
Namibia	0.0100 ***	0.0102 ***	0.0098 ***	0.0098 ***	0.0099 ***	0.0099 ***	0.0101 ***	0.0104 ***	0.0101 ***
Nigeria	0.0011	0.0013	0.0011	0.0011	0.0013	0.0012	0.0011	0.001	0.001
South Africa	0.0098 ***	0.0096 ***	0.0097 ***	0.0097 ***	0.0099 ***	0.0096 ***	0.0098 ***	0.0096 ***	0.0097 ***
Zambia	0.0019	0.0019	0.002	0.0018	0.0018	0.0021	0.0019	0.0019	0.002

Notes: *, **, and *** signify significance at 10%, 5%, and 1% levels, respectively.

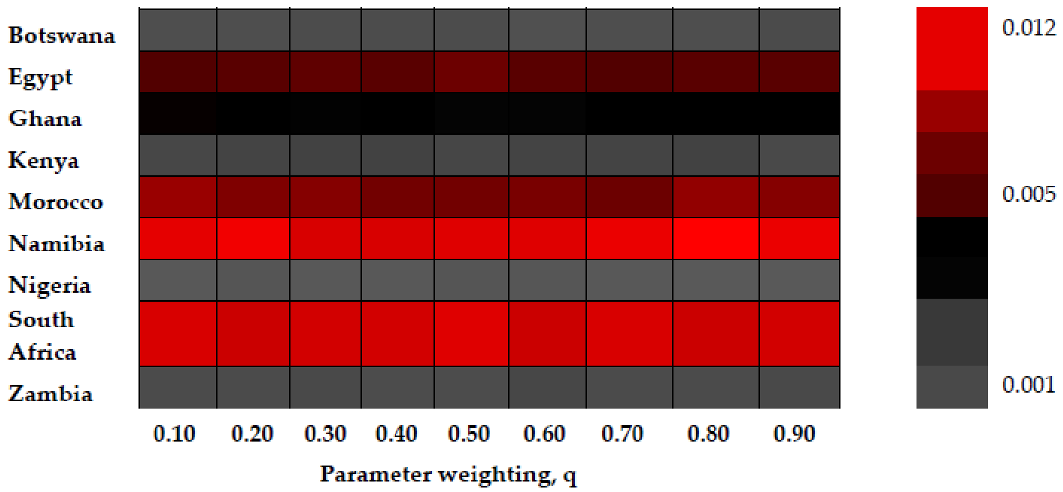

Figure 2. Heatmap of the Rényi effective transfer entropy from EPU to stock returns.

4. Discussion: The Implication for Open Innovation

The strand of economic, political, and natural phenomena in recent times resulting in a high level of economic policy uncertainty explains the current interest of research on economic policy uncertainty on economic agents. Consistent with global findings of the spillover effect of international uncertainty shocks on equity markets, a significant information flow from global uncertainty to most African stocks studied were found [18,54–56]. In particular, the finding corroborates with Belcaid and El Ghini's [37] results of the Moroccan stock market's sensitivity to economic policy uncertainty of France, Spain, and the US. This was expected as African economies heavily depend on international economies for most of their economic activities. Surprisingly, the Nigerian equity market, which ranked third in terms of market capitalization in Africa and seems to be relatively integrated into the global market, seems to be insulated from global economic uncertainty. This finding is inconsistent with the reaction of Nigeria's response to the 2009 global financial crisis but support Das and Kumar [33], saying that emerging markets are less vulnerable to international economic policy uncertainty. Notwithstanding the asymmetry in the flow of information to African stock returns, the impact of global uncertainty on equity markets is profound. The increased liberalization of financial markets in Africa has resulted in a greater integration into the global market, making the African financial market vulnerable to global uncertainty. Innovation has been argued to be central in adapting to uncertainty in times of crisis, therefore, stock markets have to innovate to minimize the impact of globalization [57].

The complexity of products and rapidly changing market demands require financial markets to enact new practices to respond to uncertainty and stay competitive [58,59]. The external search for information and its integration in the context of open innovation is one practice that can lead to increased success [58,60,61]. For example, the inability of most markets to return to pre-GFC, difficulty in overshoot in activities, following uncertainty can be attributed to a lack of innovation. In open innovation, ideas are not only exploited just inside the organization but also within the organization's boundaries.

Just as globalization has made the world a “smaller” place, innovation should be collaborative and include both internal and external ideas to withstand global uncertainty. Though financial innovation is blamed for the global financial crisis of 2009, asymmetry of information resulted in the complexity of financial products, which worsened the financial crisis [22]. Carefully selected open innovation is critical to addressing global pressures and uncertainties in international policies [62].

5. Conclusions

5.1. The Summary of This Study

This paper examines the susceptibility of the returns of African stock markets to international economic policy uncertainty and its implications for open innovation, using the daily US economic policy uncertainty index as a proxy for international economic policy uncertainty and the daily stock market index for nine African countries, namely, Nigeria Stock Exchange All Share Index (Nigeria), Nairobi All Share Index (Kenya), Zambia All Share Index (Zambia), FT/JSE All Share Index (South Africa), Ghana Stock Exchange All Share Index (Ghana), Botswana Domestic Company Index (Botswana), Casablanca All Share Index (Morocco), Namibia Stock Exchange Overall Index (Namibia), and Egypt EGX30 (Egypt) from 31 December 2010 to 27 May 2020. The results show that international economic policy uncertainty transmits significant information to all the stock markets studied, except Botswana, Kenya, Nigeria, and Zambia. The positive Rényi transfer entropy indicates that the risk about the future returns of African stocks is reduced by the knowledge of the international economic policy uncertainty. Hence, the unexpected increase in economic policy uncertainty poses a significant risk of exposure to African markets.

5.2. Implication

The findings of the study have implications for investors in terms of portfolio selection and innovation to deal with future uncertainty. The asymmetric nature of the information flow across the markets makes African stocks good candidates for both intra-Africa and international diversification of the portfolio. Increases in policy uncertainty in the US market hold significant information for the behavior of stock returns in some African markets. Market participants can use an international economic policy risk in the US as a tool to select markets for diversification of their portfolios.

The difference in response of African stock markets signifies an asymmetry of information flow within African stocks which could adversely affect the market participant and make some of the markets very vulnerable to external shock and uncertainty. Moreover, carefully selected open innovation can help African stock markets to deal with uncertainty in the global economic policy.

5.3. Limitation and Future Research Topic

Economies generally enact policies when confronted with global economic policies to mitigate its effect on the local economy. The potency of such localized policies and interventions to mitigate the global uncertainty impact the magnitude of information flow to the market and induced heterogeneity. The study assumed that the markets studied originated from homogeneous economies with no policy intervention to mitigate global uncertainty. This simplistic assumption could influence the outcome of this paper and recommend future studies to condition the influence of economic policy on domestic policy interventions like monetary policy.

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Appendix A

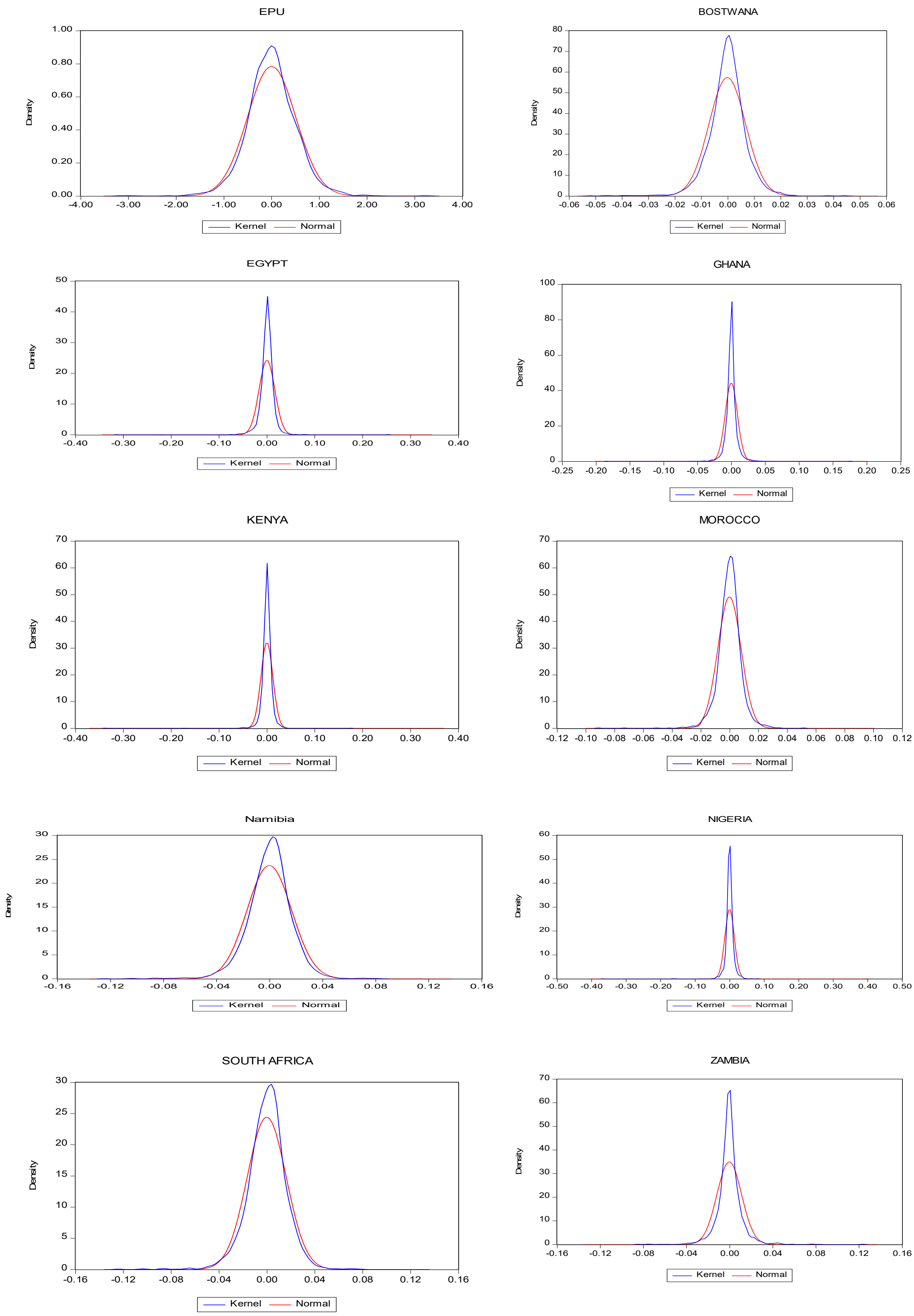

Figure A1. Kernel density plot of the return series.

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