The Study of Spillover, Risk, and Leverage Effects: Smart Beta ETF Management Style

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Abstract:

This research uses the Generalized Autoregressive Conditional Heteroscedasticity-in-Mean Autoregressive Moving Average (GARCH-M-ARMA) and Exponentially Generalized Autoregressive Conditional Heteroscedasticity-in-Mean Autoregressive Moving Average (EGARCH-M-ARMA) models to measure spillover, risk, and leverage effects of active, passive, and smart beta management Exchange-traded Funds (ETFs). The increase in popularity of ETFs and new categories within them, specifically the growth of smart beta management, means asset managers and investors have new metrics to account for when determining portfolio exposure. The results show significant relationships among all groups regarding spillover. A trend of positive multi-lateral spillover of returns among the three management types is observed with smart beta showing the highest percentage of a bi-lateral positive effect. The strongest spillover of volatility effects is among the actively managed ETFs. The testing of risk results is insignificant, but the leverage effect results are consistent with past studies showing the significant negative bi-lateral effect. These results provide evidence of the essential effects can have strategizing portfolio exposure and can be used by asset managers and investors to fine-tune and better adapt their portfolios.

Keywords: Spillover Effect, ETFs, Smart Beta, ETF Management

JEL Codes: G11, G15, G32

1. INTRODUCTION

Exchange-Traded Funds (ETFs) have continued to increase in popularity with investors and portfolio managers since their inception in 1993, even during the economic recession. In 2016, the ETF market beats out stocks in volume and value of "seven of the ten most actively traded securities on US stock markets being ETFs, not shares" (Wigglesworth, 2017). Investopedia.com reported that, according to data from ETFGI[1], 2016 global ETFs "were spread across more than 270 global providers and were listed on 64 separate exchanges throughout 51 countries" (Voros, 2016). These results from the globalization of financial markets and the current most active regions include the US, China, Japan, and the European Union/United Kingdom. Adoption of ETFs in every major market speaks to their performance and utility for investors with many investment needs. ETFs cover a variety of securities, including, but not limited to, equities, bonds, securities, and specific groups like emerging markets, derivatives, and dividend stocks. As the ETF market grows and issuers create more categories, the specific exposures that investors can seek are becoming endless. More narrow specialties of new ETFs include cryptocurrencies, blockchain innovators, ethical companies, and gender diversity. These themes in the ETF industry are collectively showing how small corners of the market can be identified and marketed as specific investments. The power of ETFs supports and encourages innovation in the global economy.

As for how they are composed, Bloomberg describes an ETF as a basket of securities that can be commodities, stocks, bonds, and any other assets that ETF companies create a fund. Investors can buy shares of these baskets and trade them in the same fashion as trading normal stocks on an exchange. The main differences lay in the asset category and management style. While asset category is extensive and increasingly vast, the management style is a relatively simple choice; Investors can choose from an actively managed fund, passively managed fund, or a middle ground referred to as smart beta.

One of the most talked about themes within the ETF space over the past few years has been a management strategy called smart beta, which is described as "a disruptive financial innovation with the potential to affect the business of traditional active management" (Kahn and Lemmon, 2016). This new management style holds a substantial portion of the ETF market with over $316 billion AUM, according to Morningstar, about 10.5% of the ETF market, as of the end of 2016. The world's largest ETF provider, BlackRock Inc., also predicts total smart beta assets will reach $1 trillion by 2020.

Management strategies for ETFs have also been popular with new approaches emerging as technologies grow. Smart beta (sometimes called strategic beta) is a fund management strategy that combines the two traditional approaches, active and passive portfolio management. The differences between these management strategies are important to investors as each has their varying specifications. Smart beta is said to occupy a space between traditional managed funds using active or passive management strategies. This new approach fills in some gaps left by saying traditional management and gives investors an option to suit their needs further when investing in ETFs. This mix of management strategies reflects a growing focus on quantitative analysis, computer learning, and program building that is aiming to manage funds with higher rates of return than the traditional manager or index trackers. While talk of the smart beta "bandwagon" and trend-marketing of the label became

[1] ETFGI LLP (2018). Available: https://etfgi.com.

a concern quickly after its rise to popularity (Marriage, 2015), the dust has settled, and smart beta is not only holding its place in the market but expanding to new areas with 2016 net inflows of $71.75 billion (Shriber, 2018).

Table 1 illustrates the definitions and clearly explains the differences between them in each management category. The expense ratios of ETFs vary, but some patterns can be observed. Passive ETFs have the lowest expense ratios due to the hands-off management style that tracks an index. Active ETFs have the highest and most extensive range of expense ratios due to the fund manager’s strategies that require time and attention from experienced individuals. Smart beta, as mentioned previously, lies in the middle of the two with some range of expenses depending on how active the quantitative analysis calibration for the index is. The performance goal characteristic is comparing the ETF’s performance of its underlying asset (with equity ETFs, usually a stock market index). Finally, transparency refers to the ability of consumers to have access to details about the ETFs management, goals, and past performance, something much less accessible in mutual funds and the most actively managed ETFs due to a sense of alpha-seeking proprietary strategy.

Table 1: ETF Management Categories

	Passive	**Active**	**Smart Beta**
Definition	Passively managed ETFs/funds seek to follow the trends of giving indexes, industries, markets, etc. These ETFs/funds often have, and sometimes seek, low volatility by creating an ETF/fund that holds the same assets as the desired index. These ETFs/funds have a beta close to 1.	Actively managed ETFs/funds are described as "alpha-seeking," meaning that management is continuously looking to exceed the ETF/fund's benchmark asset category (i.e., index, sector, etc.).	By using systematic quantitative analysis, ETFs/funds are essentially a hybrid of passive and active ETFs/funds. Smart beta seeks alpha through relatively passive means. Programmed parameters and market measurements allow for the ETF/fund to adjust to various preferences and market movements.
Expense Ratio	Low (0 ~ 0.30%)	High (0.50 ~ 1%+)	Med/Varied (0.15 ~ 0.60%)
Performance Goal	Match performance	Outperform	Outperform
Transparency	High	Low	High

Two important terms to understand when analyzing ETF management types are beta and alpha, which Picerno (2010) describes as systematic and unsystematic risk, respectively. These risk factors are a part of modern portfolio theory (MPT) which is sometimes criticized by analysts as an inevitable conflict between theoretical and applied finance. Alpha and beta have become commonly used terms as the discussion of portfolio management has shaken up by smart beta.

Beta is a market factor that is said to be inevitable by Sharpe (1964) and is ubiquitous in every security resulting in its tendency “to prevail in a diversified portfolio” (Picerno, 2010). Both authors suggest that, concerning the capital asset pricing model (CAPM), "higher investment returns only come through higher risk—beta risk" (Picerno, 2010). Beta is referred to as the amount by which security or portfolio is volatile compared to a certain benchmark, usually the market, and is the key factor present in passively managed portfolios. The beta value associated with security is on a scale greater or less than 0. As for alpha, Sharp considers this “the other” risk factor; that is everything other than beta. Every security can possess both beta and alpha risk, but only alpha can be avoided. More, alpha today is described as a portfolio manager’s ability to outperform the benchmark (underlying asset), a management style referred to as active. For this outperformance, manager compensation comes in the form of relatively high fees.

Smart beta management comes in between active and passive strategy, trying to combine the perfect amount of beta and alpha risk to outperform the underlying asset while avoiding high management costs. Kahn and Lemmon (2016) describe smart beta as “active strategies because they require periodic rebalancing to maintain the desired exposures” but spend much more time passively adjusting according to algorithms set by managers. They predict that active management will absorb new technology and use smart beta products to diversify their offerings. Because smart beta strategy uses an element of alpha-seeking through algorithmic adjustments to predict market changes or exposures, this is a product more geared towards the managers who are already running traditional active funds.

A popular topic in the investment industry is the possibility of smart beta to over-take active management and if it is a justified shift in investor preference. Many portfolio managers feel threatened by smart beta’s popularity because it can undercut prices of actively managed ETFs and provide greater transparency on methodology and risk analytics (Noël, Felix, and Véronique, 2016). It is important to look at the quantitative differences between performing these management types. This paper motivates to narrow the gap between mart beta strategies requested by investors and presented by providers.

There is extensive research on ETFs as a whole, including the effects of spillover and leverage (Chen and Huang, 2010; Chen and Diaz, 2012; Krause and Tse, 2013; Chen and Malinda; 2014; Chen, Diaz, and Chen, 2014). Studying the various effects between markets and investment tools allows investors and managers to make better-educated decisions as well as inspire and fuel innovation. As popularity has grown, the amount of academic research has increased, creating an environment where portfolio managers are developing new strategies as academics analyze new data. However, academic research on smart beta style ETFs is minimal.

This study will focus on the spillover, risk, and leverage effects between smart beta managed ETFs and their related indexes compared to ETFs under other management strategies (passive and active). The study considers the international aspect not only regarding the financial market but the ETF industry. This work will retrieve data samples from the top active markets in the world. There is little academic research available that focuses on smart beta, likely because of its recent introduction, which is why another purpose of this paper is to shed light on this new strategy and compare it to its counterparts. This paper will also illustrate a framework for distinguishing smart beta management from traditional active and passive strategies.

2. LITERATURE REVIEW

Chen and Huang (2010) studied the impact of spillover and leverage effects on returns and volatilities of stock indices and ETFs for developed and emerging markets. The authors utilized the Exponentially Generalized Autoregressive Conditional Heteroscedasticity-Autoregressive Moving Average (EGARCH-ARMA) and the Generalized Autoregressive Conditional Heteroscedasticity-Autoregressive Moving Average (GARCH-ARMA) models to analyze historical data over several periods. Their findings state that investing in emerging markets could provide a higher return than the traditional established markets and sampled ETF returns performed better than the underlying stock indices showing that performing passive funds could surpass that of popular stock indices around the world.

Chen and Diaz (2012) focused on the leverage effects of stock indices to look for the consequences on the returns and volatilities of leveraged and inverse leveraged ETFs, and the opposite. Their research provided further support of the viability of the EGARCH-M-ARMA models in measuring these kinds of effects, including spillover, one reason this research will use the same models. Their findings showed the strong positive and negative effects of their sampled ETF returns on their underlying index returns, a result providing empirical evidence that investors and fund managers must consider another important metric to determine investment strategies, specifically with leveraged and inverse leveraged ETFs.

By using Granger-causality tests, Krause and Tse (2013) revealed that US ETF returns lead those of Canada in four industry ETFs at the market level. They also showed volatility spillovers occurring bi-direction in the market, financials, and technology sectors, but only from the US to Canada for basic material and energy. Volatility feedback effects manifested themselves in bilateral spillovers in at least three of the five analyzed US ETFs. This report showed that, in contrast to prior research, return and volatility transmission across the US-Canada border continues a relevant feature of financial markets in North America. These findings, while focusing on the cross-border effects of ETFs from Canada and the US, show another aspect of ETF spillover and volatility analysis that can be beneficial to investors and managers.

Chen and Malinda (2014) analyzed the spillover, asymmetric volatility, and leverage effects of financial ETFs. From the findings, they could measure bilateral connection existing between financial and non-financial ETFs, which affects the benchmark indices, and the spillover effects of return volatilities have positive bilateral effects on stock indexes and non-financial ETFs in Canada, Europe, and the US.

In their research on the seasonal and the spillover effects of the real estate investment trust ETFs, Chen, Diaz, and Chen (2014), the findings of the spillover effects are described to have the potential to assist investors in formulating better investment strategies. By exposing possible linkages between ETFs and their underlying indices, investors and fund managers can see data that is not as clear otherwise indicating movement in either the ETF or index based on the other. Because of the large and a growing number of ETF characteristics, this kind of research has lots of potentials and varying focuses.

While these papers cover many important categories of ETFs, time periods, strategies, and different analyses of their spillover, leverage, and various effects, there is little academic concentration of the portfolio management type regarding smart beta ETFs. One of the reasons is likely due to recent beginnings, but it has occupied significant space in the market for long enough to not be considered a trend by experts. The difference between performing of active and passive managed funds can be very significant. It suggested that measuring the same effects of ETFs but updated with the addition of this new category should supply interesting results. The empirical findings could lead to changes in the approach to portfolio strategy by managers and investors.

3. DATA AND METHODOLOGY

3.1. Data

Daily average closing prices from the top equity ETFs were collected, using Yahoo Finance, within a period of individual inception to September 29th, 2017. This sample collection window was chosen to collect the largest amount of raw data available to increase the opportunity of returning significant results and capturing broad market trends. Most ETF/Index pairs begin around the late 2000s with a few exceptions running earlier or later. Because of the relatively large volume of ETFs available that focus on equity securities, this study will narrow in on the top performing and largest (net assets) equity ETFs holding securities from the USA, China, UK/Europe, and Japan markets. Table 2 lists the ETF sample data selected for this research with their market region, management type, the index they track, sample range, and the number of observations. Eight ETFs from each category of management (active, passive, smart beta) have been selected from the global markets to compare their spillover, risk, and leverage effects with their underlying stock indices. After testing returns from both the ETF and its index, management type will then compare the results to further analysis if there are any differences, and if so, their relevance to investors and portfolio managers.

ETFs of the three management styles (passive, active, smart beta) were selected based on defined lists from ETF.com and matching descriptions, beta values showing movement greater or less than the tracked index, and on expense ratios (greater than .5% being high, typical of active management) as seen in Table 1. Because there is no exact formula to determine an ETF’s management style and the definition of smart beta can be relatively arbitrary, the multiple characteristics were applied to a large sample group and ETFs that were more clearly defined through this paper’s qualifying guidelines and the publisher’s marketing of the fund were chosen for the sample.

Figure 1 shows, fund management style boxes, which are similar to those created by Morningstar, that illustrates the typical style characteristics of active and passive funds and a common, but not exclusively, the example of a smart beta fund. This image is used to provide a clearer picture of the characteristics and qualifying guidelines. This paper uses to classify the fund management style.

Table 2: ETF and Market Index Data

	Market	ETF	Index	Period	# of Observations
Active	USA	FWDD	S&P 500	12/8/11 - 09/29/17	1,462
	USA	TTFS	Russell 3000	10/5/11 - 9/29/17	1,507
	UK	CUKS	MSCI UK Small Cap	5/16/11 - 9/29/17	1,613
	EU	GREK	MSCI All Greece	12/8/11 - 9/29/11	1,462
	Japan	JPNL	MSCI Japan	6/26/13 - 9/29/17	1,075
	Japan	EZJ	MSCI Japan	6/5/09 - 9/29/17	2,096
	China	CNXT	VanEck Vect. SME-Chinext	7/24/14 - 9/29/17	804
	China	ASHR	CSI 300	11/6/13 - 9/29/17	982
Passive	USA	SPY	S&P 500	1/29/93 - 9/29/17	6,214
	USA	IWM	Russell 2000	5/26/00 - 9/29/17	4,364
	UK	EWU	MSCI UK	5/18/96 - 9/29/17	5,423
	UK	EWUS	MSCI UK Small Cap	1/26/12 - 9/29/17	1,430
	Japan	JPN	Nikkei 400 NetTotalRet.	5/26/15 - 9/29/17	579
	Japan	QJPN	MSCI JPN Fact. Mix A Capped	6/12/14 - 9/29/17	833
	China	CQQQ	AlphaSeries China Tech	1/22/10 - 9/29/17	1,937
	China	QQQC	NASDAQ OMX China Tech	1/22/10 - 9/29/17	1,937
Smart Beta	USA	MTK	Morgan Stanley Tech	9/28/12 - 9/29/17	4,274
	USA	VYM	FTSE High Div. Yield	11/16/14 - 9/29/17	2,734
	UK	QGBR	MSCI UK Factor Mix A Capped	6/12/14 - 9/29/17	831
	EU	EUMV	MSCI EU Min Vol.	6/6/14 - 9/29/17	853
	Japan	EWJ	MSCI Japan Local Index	10/18/12 - 9/29/17	1,257
	Japan	JPMV	MSCI Japan Min. Vol.	6/5/14 - 9/29/17	842
	China	YINN	FTSE China 50	12/3/09 - 9/29/17	1,968
	China	ECNS	MSCI China Small Cap	10/10/12 - 9/29/17	1,241

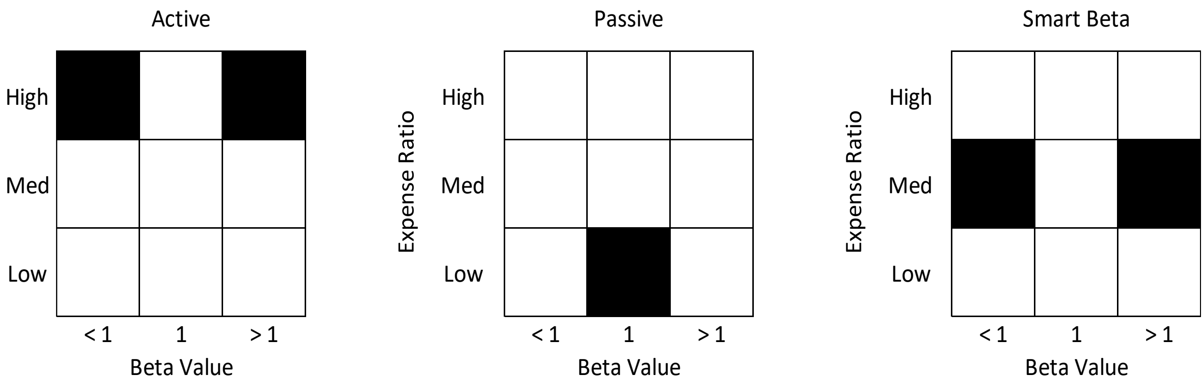

Figure 1: Management Style Boxes

3.2 Methodology

This study used a similar method to that used by Chen and Diaz (2011) in their research of the same effects focused on faith-based ETFs. The GARCH-M-ARMA and EGARCH-M-ARMA models are used to measure the spillover, risk, and leverage effects of ETFs of the specified management types with the index represented by their respected underlying assets. ETF return (R^e) measures the difference between the logarithm of the net asset value at time t and its lagged value. Market return (R^m) stands for the difference between the logarithm of the index at time t and its lagged value.

The spillover effect of returns is illustrated as follows:

$$R_{i,t}^{e} = \alpha_0 + \sum_{i=1}^{g} \alpha_i \, R_{i,t-1}^{e} + wR_{i,t-1}^{m} + \varepsilon_{i,t}^{e} + \sum_{i=1}^{s} \theta_i \, \varepsilon_{i,t-i}^{e} + zh_{i,t}^{e} \, , \tag{1}$$

$$h_{i,t}^{e} = a_0 + \sum_{i=1}^{q} a_i \varepsilon_{i,t-i}^{e^2} + \sum_{i=1}^{p} \psi_i \, h_{i,t-i}^{e} \text{ , for GARCH} \tag{2}$$

$$\log\left(h_{i,t}^{e^2}\right) = a_0 + \sum_{i=1}^{q} \left(a_0 \left| \frac{\varepsilon_{i,t-i}^{e}}{h_{i,t-i}^{e}} \right| + \delta_i \frac{\varepsilon_{i,t-i}^{e}}{h_{i,t-i}^{e}} \right) + \sum_{i=1}^{p} \psi_i \, log\left(h_{i,t-i}^{e^2}\right) \text{ , for EGARCH} \tag{3}$$

$$\varepsilon_{i,t}^{e} \mid \Psi_{t-1} \sim N\left(0, h_{i,t}^{e}\right) \, ,$$

$$R_{i,t}^{m} = \beta_0 + \sum_{i=1}^{g} \beta_i \, R_{i,t-1}^{m} + dR_{i,t-1}^{e} + \varepsilon_{i,t}^{m} + \sum_{i=1}^{s} \gamma_i \, \varepsilon_{i,t-i}^{m} + kh_{i,t}^{m} \, , \tag{4}$$

$$h_{i,t}^{m} = b_0 + \sum_{i=1}^{q} b_1 \varepsilon_{i,t-1}^{m^2} + \sum_{i=1}^{q} \delta_i \, h_{i,t-i}^{m} \text{ , for GARCH} \tag{5}$$

$$\log\left(h_{i,t}^{m^2}\right) = b_0 + \sum_{i=1}^{q} \left(b_i \left| \frac{\varepsilon_{i,t-i}^{m}}{h_{i,t-i}^{m}} \right| + \delta_i \frac{\varepsilon_{i,t-i}^{m}}{h_{i,t-i}^{m}} \right) + \sum_{i=1}^{p} \zeta_i \, log\left(h_{i,t-i}^{m^2}\right) \text{ , for EGARCH} \tag{6}$$

$$\varepsilon_{i,t}^{m} \mid \Psi_{t-1} \sim N\left(0, h_{i,t}^{m}\right) \, ,$$

where the spillover effects from market returns (R^m) and ETF returns (R^e) are represented by w and d, respectively. Spillover testing is carried out with a null hypothesis of no spillover effect of returns (w = 0; d = 0). If the w and d coefficients are distant from 0, then the lagged market and ETF returns influence each other. The risk is represented by the coefficients z and k as the standard deviations.

The model used to analyze ETF and stock index volatilities is illustrated as follows:

$$R_{i,t}^{e} = \alpha_0 + \sum_{i=1}^{g} a_i R_{i,t-i}^{e} + \varepsilon_{i,t}^{e} + \sum_{i=1}^{s} \theta_i \varepsilon_{i,t-i}^{e} + zh_{i,t}^{e} \tag{7}$$

$$h_{i,t}^{e} = a_0 + \sum_{i=1}^{q} a_i \varepsilon_{i,t-i}^{e^2} + \sum_{i=1}^{p} \psi_i \, h_{i,t-i}^{e} + v\varepsilon_{i,t-1}^{m^2} \tag{8}$$

$$\log\left(h_{i,t}^{e^2}\right) = a_0 + \sum_{i=1}^{q} \left(a_0 \left| \frac{\varepsilon_{i,t-i}^{e}}{h_{i,t-i}^{e}} \right| + \delta_i \frac{\varepsilon_{i,t-i}^{e}}{h_{i,t-i}^{e}} \right) + \sum_{i=1}^{p} \psi_i \, log\left(h_{i,t-i}^{e^2}\right) + v\varepsilon_{i,t-1}^{m^2} \tag{9}$$

$$\varepsilon_{i,t}^{e} \mid \Psi_{t-1} \sim N(0, h_{i,t}^{e}),$$

$$R_{i,t}^{m} = \beta_0 + \sum_{i=1}^{g} \beta_i \, R_{i,t-1}^{m} + \varepsilon_{i,t}^{m} + \sum_{i=1}^{s} \gamma_i \, \varepsilon_{i,t-i}^{m} + kh_{i,t}^{m} \tag{10}$$

$$h_{i,t}^{m} = b_0 + \sum_{i=1}^{q} b_1 \varepsilon_{i,t-1}^{m^2} + \sum_{i=1}^{q} \delta_i \, h_{i,t-i}^{m} + l\varepsilon_{i,t-i}^{e^2} \text{ , for GARCH,} \tag{11}$$

$$\log\left(h_{i,t}^{m^2}\right) = b_0 + \sum_{i=1}^{q} \left(b_i \left| \frac{\varepsilon_{i,t-i}^{m}}{h_{i,t-i}^{m}} \right| + \delta_i \frac{\varepsilon_{i,t-i}^{m}}{h_{i,t-i}^{e}} \right) + \sum_{i=1}^{p} \zeta_i \, log\left(h_{i,t-i}^{m^2}\right) + l\varepsilon_{i,t-1}^{e^2} \text{ , for}$$

EGARCH,

where the spillover effects of market and ETF return volatilities are denoted by v and l. The null hypothesis of this research states that the data series has an absence of the spillover effect (v=0; l=0), with the alternative hypothesis that the data series possesses the spillover effect (v $\neq$ 0; l $\neq$ 0). The sum of the coefficients for both alpha and beta is less than one showing a healthy model.

This paper aims to use these models to test the specific effects of ETFs and their underlying benchmarks to postulate useful results for investors. Based on previous studies, the results could indicate shocks in volatilities and bi-directional effects that can translate to portfolio diversification opportunity among different ETF management styles.

4. EMPIRICAL FINDINGS

4.1 Empirical Findings

Table 3 summarizes of all data sizes, period, and characteristics in the paired ETF to underlying index form. Some variance in data periods is due to the availability of performance data, lacking for indices. Note that standard deviation values reflect the volatility assumption of each management class; actively managed ETFs can be seen to have an average standard deviation around or above 2, passive remaining around a value of 1, and smart beta with a mix of low (0.729) to high (5.764). Few high values within smart beta (QGBR at 5.764 and YINN at 4.390) are due to infrequent updates in index performance, a more common occurrence with the smart beta related indices than other management styles.

While active and passive ETFs follow largely and used categorical indices of accessed historical data, many smart beta ETFs researched in this study were noticeably different. Many of the traditional active and passive ETFs are, on average, older and follow established indices. However, many smart beta ETFs are created with their underlying index, both by the same issuer. For example, the Wisdom Tree Japan Small Cap Dividend Index was created just 15 days before the DFJ ETF designed to track it (Index: 06/01/2006, ETF (06/16/2006). There is a problem when trying to collect historical data for these young and specific indices of smart beta funds as many issuers do not have listed historical prices for index performance, only related ETF performance. ETF/Index pairs with this issue were excluded from the sample.

Table 4 shows the results of various testing of the paired ETF and the underlying index, all of which will be discussed in the following paragraph. An Augmented Dickey-Fuller (ADF) unit-root test was conducted to determine stationarity in the time-series data with all samples showing significant (stationarity). In this study, a minimum Akaike Information Criterion (AIC) value, to the maximum order of (2,3), was used to identify ARMA, GARCH, and EGARCH models. The serial correlation was tested using the Breush-Godfry LM test with results revealing the inability to reject the null hypothesis for all samples or, no serial correlation. The ARCH effect was tested using the Lagrange Multiplier Test (ARCH-LM), of which, the null hypothesis of absent ARCH effect was rejected for all ETF/Index pair ARMA model results. ARCH-LM test determined ARCH error for GARCH-M-ARMA and EGARCH-M-ARMA residual values.

Table 3: Sample Size and Period of Active, Passive, and Smart Beta ETFs and Stock Indices.

Group	Market	Indices and ETFs	Mean	Std. Dev.	Skew.	Kurt.	J-Bera
Active	USA	FWDD/ S&P 500	0.041	1.542	-0.069	118.851	878,547.70 ***
	USA	TTFS/ Russell 3000	0.062	0.897	0.084	6.826	920.180 ***
	UK	CUKS/ MSCI UK Smal Cap	0.056	0.894	-1.241	14.876	7,224.913 ***
	EU	GREK/ MSCI All Greece 25/50	0.039	2.758	0.804	9.482	2,332.047 ***
	Japan	JPNL/ MSCI Japan Local	0.042	2.989	-0.347	5.804	373.359 ***
	Japan	EZJ/ MSCI Japan Local	-0.039	2.018	0.227	5.857	374.577 ***
	China	CNXT/ VanEck ChinaAMC SME	0.027	2.986	0.110	16.696	5,964.716 ***
	China	ASHR/ CSI 300	0.010	2.292	-1.353	25.853	20,432.310 ***
Passive	USA	SPY/ S&P 500	0.028	1.164	-0.115	13.307	27,503.230 ***
	USA	IWM/ Russell 2000	0.027	1.504	-0.281	7.545	3,813.250 ***
	UK	EWU/ MSCI UK	0.000	1.041	-1.712	22.243	19,976.250 ***
	UK	EWUS/ MSCI UK Small Cap	0.026	1.200	-2.731	40.072	73,365.200 ***
	Japan	JPN/Nikkei 400	0.018	1.054	-0.759	8.382	754.388 ***
	Japan	QJPN/ MSCI Japan Factor Mix A Capped	0.027	0.939	-0.814	12.267	3,069.149 ***
	China	CQQQ/ AlphaShares China Technology	0.042	1.587	-0.308	6.453	991.807 ***
	China	QQQC/ NASDAQ OMX China Technology	0.051	1.611	-0.091	7.154	869.378 ***
Smart Beta	USA	MTK/ Morgan Stanley Technology	0.012	1.710	-0.308	9.246	6,983.865 ***
	USA	VYM/ FTSE High Dividend Yield	0.033	0.729	-0.449	6.858	651.135 ***
	UK	QGBR/ MSCI UK Factor Mix A Capped	-0.016	5.764	-0.308	40.657	49,108.950 ***
	EU	EUMV/ MSCI EU Minimum Volatility	-0.002	0.891	-1.388	17.498	7,572.356 ***
	Japan	EWJ/ MSCI Japan Local	0.023	1.020	-0.207	5.748	345.232 ***
	Japan	JPMV/ MSCI Japan Minimum Volatility	0.027	0.891	0.022	5.954	304.450 ***
	China	YINN/ FTSE China 50	0.007	4.390	-0.448	5.558	563.741 ***
	China	ECNS/ MSCI China Small Cap	0.028	1.587	-0.308	20.538	15,911.68 ***

Note: *, **, and *** are significant at 10, 5, and 1%, respectively.

4.2 Spillover Effects of ETF Returns

Table 5 shows the results of the spillover, risk, and leverage effect testing using the GARCH-M-ARMA and EGARCH-M-ARMA models, bold values being significant. Analyzing the spillover effects of the ETF returns was observed. There are 37 of 48 ETF/Index pairs show an effect on the index, most of which are positive. Based on this observation, we can anticipate when many ETFs show positive returns one day. The underlying index will show positive returns the following day because of this effect. The opposite would also be true; when ETF returns perform negatively, stock index returns the following day will also perform negatively.

The smart beta results have the most bi-lateral effects out of the three management groups with 3 of 8 showing positive bi-lateral spillover on returns in both directions (ETF on Index/Index for ETF). Investors can expect this positive spillover effect between ETFs and indices to be strongest among smart beta managed ETFs. The researcher suspects that there is an explanation within the algorithmic processes carried out by both smart beta ETFs and indices. Further research into how algorithmic portfolio management can affect spillover might give insight into these effects.

These findings are relatively consistent with Chen and Diaz (2011) in that there was a greater effect of ETFs on their indices as opposed to the reverse, and that effect was predominately positive. Likely due to the specific groupings into management style coupled with a sample from various global regions, there are differences between the results of this study and some similar research.

4.3 Spillover Effects of ETF Volatilities

As with the spillover effects of returns, the spillover effect of volatilities shows predominately positive results with 19 of 24 ETF/Index pairs showing at least a unilateral positive effect, but with some mixed directions. There are many bi-lateral positive effects within each management category, more than seeing in the spillover of returns. There is stronger evidence of positive spillover effect of volatility among the sample than with the spillover of returns, but passively managed funds showed mixed results with some negative (3 of 8 ETF/Index pairs) and some mixed (3 of 8). These results are similar to those of Chen and Malinda (2014) and Chen and Diaz (2011), both also using GARCH/EGARCH-ARMA models, in that the results of spillover effects of volatilities returned a higher number of bi-lateral effects, mostly positive, than did spillover of returns.

It stands out that among actively managed funds, 4 of 8 were bi-laterally positive meaning that the spillover effect of volatility is strong among these funds and their indices and that active management styles could have a substantial spillover in their volatilities between ETFs and their underlying indices.

Table 4: Summary Statistics

	Code	ADF	ARMA	AIC	LM	ARCH LM	GARCH	AIC	ARCH LM	EGARCH	AIC	ARCH LM
Active	FWDD/	-28.34***	(0,3)	3.62	0.09	183.05***	(2,2)	3.24	0.54	(1,2)	3.17	1.24
	SP500	-20.67***	(2,3)	2.65	1.36	194.60***	(2,2)	2.33	0.26	(1,1)	2.26	0.35
	TTFS/	-38.10***	(2,3)	2.61	0.07	11.36***	(2,2)	2.51	0.51	(1,2)	2.46	0.64
	Russell3000	-39.83***	(2,2)	2.48	0.53	69.56***	(1,2)	2.30	0.13	(1,1)	2.23	0.10
	CUKS/	-21.14***	(2,2)	2.58	1.15	119.77***	(1,2)	2.37	0.26	(2,2)	2.36	0.22
	MSCI UK SC	-20.81***	(2,2)	3.07	5.79	33.46***	(1,1)	2.74	0.48	(1,2)	2.75	0.33
	GREK/MSCI	-34.78***	(2,1)	4.86	0.74	27.07***	(1,1)	4.65	0.01	(1,1)	4.65	0.13
	All Greece	-32.59***	(2,2)	4.59	0.26	8.53***	(2,2)	4.43	1.26	(2,1)	4.41	1.53
	JPNL/	-32.34***	(1,2)	5.02	0.41	22.23***	(1,2)	4.86	0.51	(1,2)	4.84	1.24
	MSCI Japan	-40.55***	(1,3)	3.08	2.52	29.15***	(1,2)	2.94	0.05	(1,1)	2.90	1.01
	EZJ/	-32.07***	(2,3)	4.22	0.25	17.29***	(2,1)	4.09	0.84	(1,2)	4.07	0.25
	MSCI Japan	-40.55***	(1,3)	3.08	2.25	29.15***	(1,2)	2.09	0.05	(1,1)	2.90	1.01
	CNXT/	-19.76***	(2,2)	4.95	3.67	70.55***	(1,1)	4.22	0.45	(2,1)	4.19	0.29
	VanEck China	-26.12***	(2,3)	4.28	0.29	39.99***	(1,2)	3.83	0.09	(2,2)	3.82	0.19
	ASHR/	-24.67***	(2,2)	4.47	2.64	6.94***	(2,1)	3.88	0.07	(1,2)	3.86	0.21
	CSI 300	-28.69***	(2,3)	3.75	0.65	59.28***	(1,1)	3.21	0.43	(1,2)	3.21	0.66
Passive	SPY/	-60.79***	(1,1)	3.13	1.24	732.54***	(2,2)	2.70	0.88	(2,2)	2.66	0.04
	SP500	-60.24***	(1,1)	3.10	1.61	606.22***	(2,2)	2.66	1.44	(2,2)	2.62	0.02
	IWM/	-70.62***	(1,2)	3.65	0.21	453.07***	(1,2)	3.33	1.51	(2,2)	3.31	0.66
	Russell2000	-70.86***	(2,0)	3.65	0.01	460.89***	(1,2)	3.33	1.27	(2,2)	3.30	0.52
	EWU/	-20.34***	(2,2)	2.91	0.17	20.59***	(2,1)	2.69	0.22	(1,2)	2.68	0.09
	MSCI UK	-19.83***	(1,2)	2.89	0.52	41.58***	(2,2)	2.62	0.11	(2,2)	2.59	0.34
	EWUS/	-33.66***	(2,2)	3.19	1.77	55.08***	(2,2)	2.92	0.23	(1,1)	2.93	0.08
	MSCI UK SC	-20.81***	(1,2)	3.06	4.15	41.93***	(2,1)	2.73	0.33	(2,2)	2.75	2.14
	JPN/	-24.17***	(2,1)	2.94	0.22	17.57***	(1,1)	2.63	0.17	(1,2)	2.63	0.63
	Nikkei 400	-24.11***	(2,1)	3.58	2.04	25.35***	(1,1)	3.20	0.27	(2,1)	3.17	0.46
	QJPN/ MSCI	-29.38***	(2,2)	2.70	0.39	14.33***	(2,0)	2.48	8.08	(2,2)	2.45	3.87
	JPN Mix	-37.07***	(0,1)	2.97	0.13	30.28***	(2,2)	2.79	0.22	(2,1)	2.77	0.95
	CQQQ/	-41.93***	(2,2)	3.75	0.25	53.93***	(1,2)	3.63	1.65	(1,2)	3.63	1.65
	AS China Tech	-37.83***	(0,1)	3.41	0.99	38.64***	(1,2)	3.24	0.84	(1,2)	3.26	0.21
	QQQC/NASDAQ	-44.14***	(2,3)	3.79	1.53	30.97***	(2,2)	3.65	4.38	(1,1)	3.65	0.58
	OMXCN	-36.82***	(1,1)	3.25	0.25	8.59***	(2,2)	3.22	0.04	(1,1)	3.21	1.02
Smart Beta	MTK/ Morgan	-49.04***	(2,3)	3.90	5.42	193.01***	(1,2)	3.43	1.29	(1,2)	3.40	0.86
	Stanley	-49.48***	(2,2)	3.93	5.33	209.05***	(2,2)	3.45	0.58	(2,1)	3.43	0.92
	VYM/	-56.96***	(1,1)	2.20	0.19	69.36***	(1,1)	1.98	0.35	(2,2)	1.93	0.24
	FTSE HY Div	-32.68***	(1,1)	2.19	0.01	95.23***	(1,1)	1.97	0.14	(2,2)	1.94	0.38
	QGBR/MSCI	-17.13***	(2,3)	5.86	1.03	55.56***	(2,1)	4.33	0.10	(1,2)	4.42	0.89
	UK Factor	-17.38***	(1,2)	3.05	6.00	27.40***	(1,1)	2.71	0.55	(2,2)	2.68	0.49
	EUMV/ MSCI	-29.38***	(2,2)	2.60	0.03	10.11***	(2,2)	2.43	0.11	(2,1)	2.42	0.25
	EU Min Vol	-32.46***	(1,2)	2.60	0.34	40.33***	(1,1)	2.42	0.08	(2,2)	2.38	0.18
	EWJ/ MSCI	-36.91***	(2,2)	2.86	0.09	29.97***	(2,1)	2.70	0.88	(1,2)	2.68	1.25
	JPN Local	-40.55***	(1,3)	3.08	2.46	28.96***	(2,2)	2.95	0.33	(2,1)	2.91	0.24
	JPMV/ MSCI	-30.01***	(1,1)	2.60	0.31	2.30***	(2,1)	2.47	0.09	(1,2)	2.45	0.72
	JPN Min Vol	-44.42***	(0,1)	2.84	0.29	33.62***	(2,2)	2.68	0.22	(2,2)	2.67	0.62
	YINN/	-44.29***	(2,2)	5.79	0.48	74.77***	(2,2)	5.64	3.95	(2,1)	5.64	3.11
	FTSE China 50	-41.66***	(2,1)	3.50	0.36	30.41***	(2,2)	3.36	0.08	(1,2)	3.35	0.72
	ECNS/ MSCI	-35.39***	(2,2)	3.76	1.57	166.30***	(2,1)	3.37	0.05	(1,1)	3.37	0.66
	China SC	-29.88***	(2,3)	3.22	0.59	68.22***	(1,1)	2.69	0.29	(1,2)	2.69	0.25

Note: ADF stands for the t-statistic for the Augmented Fuller test with a constant and trend at the level. LM is Breusch-Godfrey serial correlation test with Lag (4) for examining the best lag-period. *, **, and *** are significant at 10, 5, and 1%, respectively.

4.5 The relationship between Risk and Returns

In Table 6, the results of testing for the relationship between risk and returns (denoted by k and z) returned mostly insignificant data, consistent with the findings of Chen and Melinda (2014). There are a few significant effects among active. ETF FWDD has a positive effect on its underlying index, S&P 500, while ETF JPNL has a negative effect on its underlying index, MSCI Japan Local. Based on the results from this sample, there is not enough evidence to suggest a relationship, whether negative or positive, between risk and return.

4.6 Relationship between Leverage and Returns

As with Chen and Melinda (2014), almost all results from the leverage effect testing returned as negative and bilateral, except mixed results among active management (GREK/MSCI All Greece, EZJ/MSCI Japan, CNXT/VanEck China, and ASHR/CSI300), one among passive management (CQQQ/NASDAQ), and one among smart beta (YINN/FTSE China 50). It is worth mentioning that most of these outliers also returned abnormal results in spillover testing as well, suggesting that the data may differ from the norm in some way. Significant, negative, and bi-lateral results are seen in 18 of 24 ETF/Index pairs meaning, as shown in Table 6.

4.7 Relationship with Theoretical Theories

The empirical results of this research and their significance to the investment community are related to the theory of Adaptive Market Hypothesis (AMH), specifically the concept of Adaptive Investment Approach (AIA). This approach to portfolio management and investment strategy is a challenge to the Efficient Markets Hypothesis that suggests market pricing "incorporates all information rationally and instantaneously" (Lo, 2004). AMH, detailed in Andrew Lo's 2004 research. The Adaptive Markets Hypothesis: Market Efficiency from an Evolutionary Perspective, says that pricing of market assets is contributing to "individuals adapting to a changing environment," in other words, asset managers using data and forecasting to adjust their market exposure. This relationship also involves the Noisy Market Hypothesis, another different theory of EMH. Siegel (2006) argues that security prices are not always the best approximation of a firm's value, suggesting that speculators and momentum traders, larger influence on the prices, muddying the accuracy of firm value by security price through what he calls "noise."

This sociological and evolutionary psychology perspective on financial market efficiency suggests that the available data, like the empirical results of this research, will add to the individual's decision-making process and effect on market pricing through adaptation. With new data processing tools and strategies that give managers and investors greater insight into specific metrics, these alternative theoretical approaches to financial behavior will likely increase in relevance.

Table 5: Spillover effects of returns, and volatilities for Active, Passive, and Smart Beta ETFs and Indices (Cont. on next page).

	Code	**Spillover Effects of Returns**				**Spillover Effects of Volatilities**			
		GARCH-M-ARMA		EGARCH-M-ARMA		GARCH-M-ARMA		EGARCH-M-ARMA	
		Index	ETF	Index	ETF	Index	ETF	Index	ETF
		d	*w*	*d*	*w*	*l*	*v*	*l*	*v*
Active	FWDD/ SP500	0.005 (0.654)	**0.980** **(0.000)*** **	-0.002 (0.895)	**0.942** **(0.000)*** **	**-0.515** **(0.000)*** **	**0.157** **(0.000)*** **	0.001 (0.337)	**-0.006** **(0.000)*** **
	TTFS/ Russell 3000	**0.896** **(0.000)*** **	-0.001 (0.988)	**0.903** **(0.000)*** **	0.023 (0.445)	**0.628** **(0.000)*** **	**-0.246** **(0.000)*** **	**0.017** **(0.051)* **	**0.612** **(0.000)*** **
	CUKS/ MSCI UK SC	0.034 (0.505)	**0.064** **(0.036)* **	**0.075** **(0.057)* **	**0.071** **(0.017)* **	**0.868** **(0.000)*** **	**0.070** **(0.006)** **	**0.006** **(0.038)* **	**0.009** **(0.039)* **
	GREK/ MSCI All Greece	**-0.395** **(0.000)*** **	**-0.252** **(0.000)*** **	**-0.336** **(0.000)*** **	**-0.269** **(0.000)*** **	**0.363** **(0.000)*** **	**0.371** **(0.000)*** **	**0.002** **(0.006)** **	-0.000 (0.742)
	JPNL/ MSCI Japan	**0.246** **(0.000)*** **	**0.159** **(0.051)* **	**0.246** **(0.000)*** **	**0.215** **(0.016)* **	**0.038** **(0.000)*** **	**-0.337** **(0.000)*** **	**0.015** **(0.000)*** **	**-0.001** **(0.008)** **
	EZJ/ MSCI JPN	**-0.356** **(0.000)*** **	**-0.125** **(0.028)* **	**-0.342** **(0.000)*** **	-0.139 (0.023)	**0.183** **(0.000)*** **	**0.149** **(0.000)*** **	-0.001 (0.870)	0.000 (0.885)
	CNXT/ VanEck China	**0.245** **(0.000)*** **	0.045 (0.410)	**0.231** **(0.000)*** **	0.022 (0.724)	**0.016** **(0.019)* **	-0.020 (0.574)	0.000 (0.556)	-0.000 (0.512)
	ASHR/ CSI 300	**0.133** **(0.000)*** **	-0.047 (0.582)	**0.159** **(0.000)*** **	0.090 (0.216)	**0.287** **(0.000)*** **	**0.073** **(0.078)* **	0.000 (0.934)	**0.003** **(0.001)*** **
Passive	SPY/ SP500	**0.646** **(0.000)*** **	-0.005 (0.793)	**0.569** **(0.000)*** **	-0.024 (0.287)	**0.343** **(0.000)*** **	**-0.097** **(0.000)*** **	**0.004** **(0.002)** **	**0.005** **(0.001)** **
	IWM/ Russell2000	**0.276** **(0.000)*** **	0.067 (0.402)	**0.312** **(0.000)*** **	0.103 (0.207)	**-0.754** **(0.000)*** **	**-0.060** **(0.004)** **	**0.006** **(0.000)*** **	**0.005** **(0.000)*** **
	EWU/ MSCI UK	**-0.087** **(0.000)*** **	**-0.105** **(0.006)** **	**0.486** **(0.000)*** **	**-0.078** **(0.059)* **	**-0.554** **(0.000)*** **	**0.068** **(0.000)*** **	0.008 (0.365)	**0.010** **(0.000)*** **
	EWUS/ MSCI UK SC	**0.289** **(0.000)*** **	**0.457** **(0.000)*** **	**0.297** **(0.000)*** **	**0.412** **(0.000)*** **	**-0.162** **(0.032)* **	0.330 (0.306)	0.006 (0.141)	**0.019** **(0.000)*** **
	JPN/ Nikkei 400	**0.171** **(0.010)** **	**0.061** **(0.091)* **	**0.173** **(0.006)** **	0.048 (0.229)	**1.645** **(0.002)** **	**0.048** **(0.000)*** **	-0.005 (0.229)	**-0.006** **(0.001)*** **
	QJPN/ MSCI JPN Mix	**0.440** **(0.000)*** **	**0.129** **(0.000)*** **	**0.403** **(0.000)*** **	**0.206** **(0.000)*** **	**0.457** **(0.000)*** **	**0.176** **(0.000)*** **	-0.008 (0.328)	**0.008** **(0.002)** **
	CQQQ/ AS China Tech	0.010 (0.595)	**-1.022** **(0.000)*** **	0.014 (0.475)	**-1.031** **(0.000)*** **	**0.025** **(0.000)*** **	**-0.617** **(0.000)*** **	**0.012** **(0.000)*** **	**0.011** **(0.001)*** **
	QQQC/ NASDAQ OMXCN	-0.014 (0.549)	0.017 (0.635)	-0.018 (0.438)	0.017 (0.626)	**-3.141** **(0.001)** **	-0.006 (0.400)	0.011 (0.264)	0.002 (0.577)

	Code	**Spillover Effects of Returns**				**Spillover Effects of Volatilities**			
		GARCH-M-ARMA		EGARCH-M-ARMA		GARCH-M-ARMA		EGARCH-M-ARMA	
		Index	ETF	Index	ETF	Index	ETF	Index	ETF
		d	*w*	*d*	*w*	*l*	*v*	*l*	*v*
Smart Beta	MTK/ Morgan Stanley	0.035 (0.368)	**0.880 (0.000)*****	0.061 (0.229)	**0.778 (0.000)*****	**-0.045 (0.022)***	**-0.332 (0.000)*****	0.002 (0.008)	0.002 (0.004)
	VYM/ FTSE HY Div	**0.544 (0.000)*****	**-0.090 (0.056)***	**0.548 (0.000)*****	-0.075 (0.112)	**0.603 (0.000)*****	**0.339 (0.000)*****	0.035 (0.105)	**0.046 (0.061)***
	QGBR/ MSCI UK Factor	**-0.017 (0.000)*****	**0.543 (0.000)*****	**-0.008 (0.033)**	**0.614 (0.000)*****	**0.767 (0.000)*****	**0.233 (0.000)*****	-0.006 (0.698)	**-0.004 (0.000)*****
	EUMV MSCI EU Min Vol	**0.6360 (0.000)*****	0.038 (0.431)	**0.596 (0.000)*****	0.033 (0.564)	**0.215 (0.000)*****	**-1.998 (0.000)*****	0.021 (0.294)	-0.016 (0.347)
	EWJ/ MSCI JPN Local	**0.726 (0.000)*****	**0.044 (0.000)*****	**0.709 (0.000)*****	**0.058 (0.035)***	**0.355 (0.000)*****	-0.022 (0.739)	**0.131 (0.000)*****	-0.010 (0.033)
	JPMV/ MSCI JPN Min Vol	**0.415 (0.000)*****	**0.111 (0.000)*****	**0.420 (0.000)*****	**0.098 (0.001)*****	-0.933 (0.104)	**0.064 (0.002)****	-0.003 (0.803)	0.005 (0.533)
	YINN/ FTSE China 50	0.007 (0.452)	**-2.352 (0.000)*****	0.005 (0.603)	**-2.317 (0.000)*****	**0.004 (0.000)*****	**0.836 (0.042)***	**0.001 (0.000)*****	0.000 (0.352)
	ECNS/ MSCI China SC	**0.160 (0.000)*****	**0.557 (0.000)*****	**0.180 (0.000)*****	**0.698 (0.000)*****	**0.030 (0.000)*****	**0.586 (0.000)*****	**0.004 (0.009)****	**-0.008 (0.000)*****

Note: ( ) stands for p value and *, **, and *** are significant at 10, 5, and 1%, respectively.

Table 6: Risk and volatility results for Active, Passive, and Smart Beta ETFs and Indices

Group	Risk				Leverage	
	GARCH-M-ARMA		EGARCH-M-ARMA		EGARCH-M-ARMA	
	Index	ETF	Index	ETF	Index	ETF
	k	*z*	*k*	*z*	*δ*	*δ*
Active	**0.159 (0.057)***	**0.353 (0.000)*****	0.131 (0.117)	**0.213 (0.000)*****	**-0.233 (0.000)*****	**-0.221 (0.000)*****
	-0.010 (0.858)	**0.458 (0.000)*****	0.042 (0.391)	0.071 (0.519)	**-0.240 (0.000)*****	**-0.085 (0.000)*****
	-0.251 (0.015)*	0.003 (0.980)	-0.117 (0.307)	0.186 (0.137)	**-0.070 (0.001)*****	**-0.155 (0.000)*****
	-0.088 (0.288)	0.046 (0.615)	0.077 (0.370)	0.061 (0.465)	**-0.039 (0.022)***	0.018 (0.246)
	-0.050 (0.364)	**-0.287 (0.000)*****	-0.055 (0.303)	-0.059 (0.536)	**-0.114 (0.000)*****	**-0.061 (0.000)*****
	-0.020 (0.703)	0.026 (0.790)	-0.0717 (0.196)	-0.018 (0.860)	**-0.114 (0.000)*****	**0.073 (0.005)****
	0.066 (0.470)	0.027 (0.730)	0.001 (0.996)	0.063 (0.620)	0.003 (0.750)	**-0.127 (0.005)****
	0.024 (0.752)	**0.356 (0.055)***	0.058 (0.435)	-0.019 (0.795)	0.014 (0.224)	**0.054 (0.000)*****
Passive	**0.039 (0.034)***	**0.066 (0.069)***	0.014 (0.465)	0.020 (0.542)	**-0.158 (0.000)*****	**-0.169 (0.000)*****
	0.127 (0.003)**	**0.134 (0.011)***	**0.065 (0.0812)***	0.068 (0.137)	**-0.125 (0.000)*****	**-0.126 (0.000)*****
	0.108 (0.139)	-0.053 (0.649)	0.030 (0.690)	-0.144 (0.149)	**-0.204 (0.000)*****	**-0.141 (0.000)*****
	-0.202 (0.0352)*	**-0.176 (0.010)***	-0.085 (0.420)	**-0.164 (0.039)***	**-0.026 (0.008)****	**-0.077 (0.000)*****
	-0.097 (0.389)	-0.118 (0118)	-0.098 (0.378)	0.020 (0.866)	**-0.131 (0.000)*****	-0.024 (0.153)
	0.015 (0.889)	0.038 (0.629)	0.087 (0.440)	0.003 (0.974)	**-0.140 (0.000)*****	**-0.058 (0.000)*****
	0.058 (0.607)	0.021 (0.622)	0.150 (0.171)	0.037 (0.417)	**0.063 0.000)*****	**-0.058 (0.000)*****
	0.168 (0.597)	0.188 (0.147)	0.183 (0.502)	0.143 (0.320)	**-0.081 (0.000)*****	**-0.031 (0.001)****
Smart Beta	0.031 (0.441)	0.005 (0.661)	-0.020 (0.613)	0.003 (0.881)	**-0.086 (0.000)*****	**-0.008 (0.000)*****
	0.176 (0.013)*	**0.288 (0.030)***	**0.11 (0.075)***	0.168 (0.251)	**-0.137 (0.000)*****	**-0.163 (0.000)*****
	-0.036 0.704	**-0.057 (0.000)*****	-0.186 (0.119)	**0.100 (0.020)***	**-0.228 (0.000)*****	**-0.141 (0.000)*****
	0.126 (0.136)	0.040 (0.813)	0.061 (0.481)	-0.076 (0.567)	**-0.261 (0.000)*****	**-0.114 (0.000)*****
	-0.046 (0.397)	-0.214 (0.796)	0.045 (0.642)	**-0.113 (0.057)***	**-0.157 (0.000)*****	**-0.071 (0.000)*****
	0.087 (0.466)	0.032 (0.772)	0.152 (0.196)	-0.039 (0.705)	**-0.127 (0.000)*****	**-0.047 (0.006)****
	0.006 (0.957)	-0.009 (0.873)	0.073 (0.469)	0.001 (0.991)	**0.048 (0.000)*****	**-0.046 (0.005)****
	0.080 (0.427)	0.079 (0.288)	0.024 (0.789)	**-0.110 (0.000)*****	**-0.070 (0.000)*****	**-0.024 (0.003)****

Note: *, **, and *** are significant at 10, 5, and 1%, respectively.

5. Conclusion

This study looks at the relationship between ETFs and their underlying indices comparing global ETFs from three main management styles (active, passive, and smart beta) using the GARCH-M-ARMA and EGARCH-M-ARMA models to measure spillover, risk, and leverage effects of returns and volatilities. Results from the eight ETF/Index pairs in each management group (two from four major global markets; the US, UK/Europe, China, Japan) were varied, but some trends can be identified.

ETF investors have several options to choose from when looking to diversify market exposure and what this study has shown is that the ETF/fund management style is one factor involved. The sample of funds from all over the world chosen for this study shows significant spillover and the leverage effect between the ETFs and their underlying indices, information that should be considered when strategizing investment exposure. The positive spillover effect of returns is widespread across the three management styles and global regions, but with smart beta, management returning the highest percentage of bi-lateral positive spillover effect. The positive spillover effect of volatility is relatively stronger with more bi-lateral results and active management returning the most significant indication of bi-lateral spillover. While the results of risk testing were insignificant, the leverage effect results were consistent with past research and showed a strong negative bi-lateral trend.

A recommendation for those looking to invest in ETFs is to consider fund management styles with an updated perspective as opposed to either passively managed with simple algorithms designed to track indices or expensive and risky proprietary strategy with little transparency. Management is changing as rapidly as the financial industry itself, with new technology, creating new categories of management. The industry trend is to force an ETF into one of the previously defined categories, passive or active, but new data suggest that there is the increasingly significant difference between management strategies as managers adopt new technologies. These new differences in strategy should be a factor in deciding which ETFs will fit best within a portfolio. As this study suggests, closely observing an ETFs underlying index and anticipating various spillover and leverage effect can help to create better and more precise exposure for a portfolio.

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