Topic: Comparative Performance of US Sectoral Exchange Traded Funds

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Abstract

This study evaluates the performance of sectoral exchange-traded funds (ETFs) in the U.S. stock market using a frontier distance directional model, which assigns varying weights to risk (average daily downside deviation) and return (average daily return and upside deviation). To enable meaningful comparison, risk and return components were calculated using average daily data over periods ranging from 3 to 24 years for each ETF. While the performance rankings of some ETFs vary over time—particularly under extreme scenarios—certain ETFs remain consistently efficient regardless of risk-return preferences. The study also proposes a flexible framework for assessing short-, medium-, and long-term inefficiencies under different risk-return weightings. Results show that XLV (11-year), XLF (14- and 24-year) maintain full efficiency across all risk-return scenarios. In contrast, XLU and XLF rankings decline as more weight is assign to risk, while XLI, XLB, and XLF rankings improve under the same condition.

Keywords: Exchange Traded Funds, technical efficiency/inefficiency, Weighted Russel Directional Distance model, upside deviation, downside deviation and returns.

1. Introduction

Stock market investment is one of the key contributors to economic growth and development (Pandya & Sisombat, 2017). Passive investing has gained considerable popularity due to its cost-effectiveness, simplicity, diversification benefits, transparency, and long-term orientation. Exchange-traded funds (ETFs) have recently emerge as one of the popular sources of passive income among both regular and professional investors (Ben-David et al., 2017). ETFs are defined as a basket of securities that constitute an index which can be bought or sold through a brokerage firm on the stock exchange market. They are regarded as an open-end investment vehicle that replicates the risk and return profile of their corresponding benchmark indices (Gastineau, 2002; Tsolas, 2022). Given their cost-effectiveness, transparency, liquidity and tax advantage, ETFs provide diversified benefits and indirect exposure to foreign stocks that would otherwise be out of reach (Bowes & Ausloos, 2021; Dragomirescu-Gaina et al., 2021; Henriques et al., 2022; Tsolas, 2022).

In 1993, State Street Global Advisors launched the first US-listed ETF, Standard and Poor's Depository Receipts (SPDR) trust (SPY), which tracks the standard and poor’s (S&P) 500 index (Heidari et al., 2011). After the successful execution of SPY, more ETFs were introduced, including sectoral ETFs and others that track major indices such as NASDAQ. In the early 2000s, the ETF market expanded quickly, with a wide range of funds introduced, including those for bonds, international stocks, commodities and various sectors and investment strategies.

ETFs represent a remarkable innovation in modern finance, revolutionizing the stock market landscape since their inception. Introduced in Canada and the U.S during the early 1990s, ETFs have experienced continuous expansion. For instance, their assets under management (AUM) surged from USD 1.3 billion in 2010 to an impressive USD 7.7 billion in 2021 (Magner et al., 2022). By the close of 2021, ETFs comprised 16 percent of the U.S. stock market capitalization, surpassing the 14 percent held by the mutual fund industry (Magner et al., 2022). According to Henriques et al. (2022), the total net assets of U.S. ETFs soared from US$2.1 trillion in 2015 to US$4.4 trillion in 2019. Forecasts from Bank of America project a staggering growth trajectory for the U.S. ETF market, estimating it to reach an impressive

US$50 trillion by 2050 (Henriques et al., 2022). This meteoric rise in ETFs underscores their pivotal role in the financial markets.

ETFs provide liquidity across nearly all sectors of the financial markets, enabling investors of all sizes to build institutional-quality portfolios at significantly lower management costs than traditional mutual funds (Hill et al., 2015). ETFs are accountable for risk transfer and distribution, information transparency, price discovery, and the development of a competitive market. Due to their role in providing liquidity access across all sectors of the financial market and their accountability for risk transfer and information transparency, examining the performances and technical efficiency of ETFs has attracted attention among scholars (Chu et al., 2010; Elton et al., 2019; Tsolas, 2011; Tsolas & Charles, 2015).

In the stock market, investors seek to optimize their portfolios by selecting high-performing stocks and funds, assessing them through various risk-return trade-off measures. The Sharpe ratio is one of the most commonly used traditional measures in the finance literature (Sharpe, 1964). The Sharpe ratio, a cornerstone of the risk-adjusted mean-variance framework rooted from the work of Markowitz (1959), uses estimated beta or standard deviation to evaluate portfolio performance (Valadkhani & Moradi-Motlagh, 2023). However, it does not explicitly account for downside risk or upside return. As a result, investors increasingly focus on extreme downside risks, leading to the popularity of alternative measures like the Sortino ratio (Sortino & Forsey, 1996; Sortino & Van Der Meer, 1991) and drawdown measures including the Calmar, Sterling, Burke, and Pain ratios (Schuhmacher & Eling, 2011).

Various measures are used to assess the risk-adjusted performance of portfolios. DEA is particularly an effective tool for evaluating the performance of DMUs (Emrouznejad & Yang, 2018). It is widely applied to calculate efficiency scores across a range of industries and sectors

(Barros & Leach, 2006; Henriques et al., 2022; Nemoto & Goto, 1999; Valadkhani & Moradi-Motlagh, 2023).

One key benefit of the DEA model is its ability to handle multiple inputs and outputs when calculating efficiency scores. Thus, it's crucial to account for both downside and upside risks, along with returns, when evaluating the performance of sectoral ETFs. Blume (1970) points out that the Markowitz (1959) portfolio optimization framework prioritizes risk and expected return, aiming for an optimal balance. It's important to recognize that investors have varying tolerances for risk and return (Hoffmann & Post, 2017). Therefore, it's vital to analyse which US sectoral ETFs are technically efficient by considering the risk and return preferences of different investors.

This study contributes to literature by ranking sectoral ETFs according to various risk and return preferences, an approach not considered by traditional performance measures. This allows investors to tailor their portfolios to minimize risk and maximize returns. The study also analyses the performance of sectoral ETFs over different time horizons, ranging from 3 to 24 years. This enables investors understand the best times to invest in specific sectors, determining whether they perform better in the long run or in the short run. In the finance literature, non-parametric methods like DEA are widely used to rank the performance of DMUs. Introduced by Charnes et al. (1978), DEA uses mathematical programming to assess DMUs' performance. It also helps identify benchmarks for inefficient units, offering managers critical guidance on best practices.

This study enables investors to tailor their investment decisions according to the risk-return preferences considered in the analysis. It explores how these preferences affect the ranking of ETFs through the proposed efficiency model, promoting a more customized approach to investment strategies. Additionally, the study evaluates the relative performance of sectoral ETFs using a non-radial measure of technical inefficiency derived from the directional distance model. In essence, it addresses the following research questions:

1. What is the relative performance of sectoral ETFs in the US stock market?
2. Which sectoral ETFs should extreme risk averse, extreme risk lover and risk neutral investors invest in?
3. Which sectoral ETFs are the best performing sector in short, medium and long run?

Tsolas (2011) conducted a comprehensive study to evaluate the performance of natural resources ETFs using a two-stage DEA approach. The primary objective of this research was to assess the relative efficiency of a sample of sectoral ETFs. In the first stage, the study employed the Generalised Proportional Distance Function (GPDF) within the DEA framework to measure the relative performance of the ETFs. Subsequently, in the second stage, the Tobit model was employed to analyse the determinants of efficiency scores obtained from the first stage. The findings of the study revealed that approximately half or more of the sampled funds exhibited potential for efficiency improvement. This inefficiency could be attributed to various factors, including the beta coefficient and fund persistence. The study's results underscore the importance of these variables in explaining fund performance, providing valuable insights for investors and fund managers aiming to enhance the efficiency of natural resources ETFs.

In frontier analysis, the most efficient investment funds are those that effectively balance maximizing returns with minimizing risk. Luenberger (2002) introduced an approach that evaluates a portfolio's returns and volatility by minimizing its distance from the Markowitz efficient frontier. Building on this, Devaney et al. (2016) examined the trade-off between risk and return by measuring how far a fund's observed performance deviates from a quasi-Markowitz frontier, given a specific directional vector. Similarly, Buetow and Henderson (2012) outlined a common portfolio management strategy focused on optimizing asset allocation among various risk categories, taking into account their respective risk-return profiles. Other researchers, including Murthi et al. (1997), Basso and Funari (2001) and Lamb and Tee (2012), highlighted the role of net returns (adjusted for expense ratios) and differences in risk as key considerations influencing investor decisions when selecting ETFs. These factors are integral to the weighting methods proposed in this study, which will be detailed in the next section.

ETFs were chosen over individual stocks due to their composition of a large number of stocks, which reduces the idiosyncratic characteristics specific to a firm resulting from market overreactions to news, mergers, and acquisitions. ETFs are recognized as a cost-effective means of diversification across various asset classes (Easley et al., 2021; Lettau & Madhavan, 2018) and have the potential to significantly impact the broader investment landscape. Lettau and Madhavan (2018) assert that ETFs are among the most significant financial innovations in decades, tracking diverse domestic and international indices, as well as more specialized sector, region, or country indices, with the potential to reshape the overall investment landscape dramatically.

2. Methodology

The DEA approach assesses the efficiency of a collection of DMUs based on chosen inputs and outputs, categorizing them as efficient or inefficient. It also aids in identifying benchmarks for inefficient DMUs, offering insights into best practices. This method has been used to evaluate financial performance, overcoming limitations of traditional measures (Choi & Min, 2017; Murthi et al., 1997). Each inefficient DMU is evaluated relative to efficient counterparts within the same category, while considering multiple inputs and outputs simultaneously.

Chen et al. (2015) introduced the WRDDM, a non-radial measurement of technical inefficiency that incorporates weighted variables for specific inputs and outputs. Barros et al. (2012) pioneered the application of the WRDDM framework to banking efficiency analysis, which has since been widely adopted in subsequent studies (Fuentes et al., 2020; Fujii & Managi, 2013; Fujii et al., 2018; Johnstone et al., 2017; Liu & Feng, 2019; Saleh et al., 2020; Vilvanathan, 2020). The WRDDM's capability to assign different weights to individual inputs and outputs makes it a highly applicable model for estimating the efficiency of ETFs, stocks, and portfolios with varying risk and return preferences.

This study employs WRDDM at various risk and return appetite. The WRDDM is specified as follows:

Suppose that there are N sectoral ETFs that use I risk factors (x) to produce O outputs (y). According to Chen et al. (2015), the model for the estimation of the inefficiency score for the kth DMU is given by:

$$D\,(X_{K\,,}Y_k) = \text{Max}\,(w_x(\textstyle\sum_{i=1}^{I} w_i^x\, \emptyset_i^k) + \; w_y(\textstyle\sum_{o=1}^{O} w_O^Y\, \sigma_O^k)$$

Subject to

$\sum_{n=1}^{N} \gamma_n \, x_{in} \leq \; x_{ik} \, (1 - \; \emptyset_i^k)$ i = 1,…,I

$\sum_{n=1}^{N} \gamma_n \, y_{on} \geq \; y_{ok} \, (1 + \; \sigma_o^k)$ o = 1,…,O

$\gamma_n \geq 0$, n = 1, 2,…, N (1)

Where t $\emptyset_i^k$, $and \; \sigma_o^k$ represent the inefficiency scores associated with individual inputs and outputs, respectively. The parameters w_x, and w_y denote the overall weights assigned to inputs and outputs, while $w_i^x$and w_i^yspecify the weights allocated to each corresponding input and output. When the directional distance function D(x,y,b) = 0, the ETF is considered technically efficient, indicating that no improvements are necessary. Conversely, a value of D(x,y,b)>0 greater than zero signifies the existence of inefficiency. The sources of such inefficiency can be identified by examining the inefficiency levels of individual inputs and outputs; a positive inefficiency score implies that the corresponding input or output contributes to the overall inefficiency

The model proposed in this study incorporates risk appetite components (downside risk) w_x, ranging from 10% to 90%, and return components (return and upside deviation) w_y ranging from 10% to 90%, as shown in Table 1. Each sectoral ETF is divided into components spanning three to twenty-four years of average daily return, upside deviation, and downside deviation. For example, XLK is divided into twenty-two components, ranging from 3-year XLK to 24-year XLK. The objective is to minimize downside deviation (a proxy for risk) and maximize average daily return and upside deviation (proxies for return). Our analysis is based on the assumption that the summation of input and output weights should be unity, as depicted in Table 1.

Table 1

Alternative weights for w_x and w_y in five different investment scenarios

Risk and return preference	Input weights (w_x)	Output weight (w_y)
Extreme high return	0.1	0.9
Very high return	0.2	0.8
High return	0.3	0.7
Moderate return	0.4	0.6
Balance	0.5	0.5
Moderate risk	0.6	0.4
Risk averse	0.7	0.3
Very risk averse	0.8	0.2
Extreme risk averse	0.9	0.1

Note: This table shows the various weights assigned to inputs and outputs

By incorporating the alternative weights in Table 1, the proposed model can be written as:

D (X_{K}, Y) = Max $(w_x(\emptyset_1^k) + w_y(0.5\sigma_1^k + 0.5\sigma_2^k))$

Subject to

$\sum_{n=1}^{N} \gamma_n \, x_{1n} \leq x_{1k} \, (1 - \emptyset_1^k)$

$\sum_{n=1}^{N} \gamma_n \, y_{1n} \geq y_{1k} \, (1 + \sigma_1^k)$

$\sum_{n=1}^{N} \gamma_n \, y_{2n} \geq y_{2k} \, (1 + \sigma_2^k)$

$\gamma_n \geq 0.$ (2)

To determine the inefficiency scores of ETFs, Eq. (2) must be applied iteratively nine times with varying weights. This iterative process enables the assessment of each ETF under diverse risk and return preferences relative to its counterparts. In some cases, ETFs may exhibit super-efficiency, consistently achieving the highest net returns while maintaining the lowest inefficiency scores.

The WRDDM offers distinct advantages over conventional performance evaluation methods. It facilitates the simultaneous adjustment of individual input and output variables, thereby providing a more precise depiction of actual production processes. This approach allows for the joint consideration of returns and risks when evaluating the performance of ETFs. In addition, the model supports the allocation of varying weights to inputs and outputs over different time horizons, aligning with the diverse risk-return preferences of investors in their decision-making processes. As a result, the WRDDM delivers a more comprehensive assessment of ETF performance compared to traditional metrics such as the Sharpe and Sortino ratios.

2.1 Data for the analysis

This study defines average daily return and upside deviation as outputs, while downside deviation serves as an input proxy. The DEA analysis employs daily data from January 1, 1999, to December 31, 2022, obtained from Yahoo Finance. The focus is on sectoral ETFs under the SPDR brand by State Street Global Advisors. The sectoral ETFs analysed include: XLK (Technology), XLE (Energy), XLF (Financial), XLP (Consumer Staples), XLB (Materials), XLI (Industrial), XLY (Consumer Discretionary), XLV (Healthcare), and XLU (Utility). The ETFs XLRE (Real Estate Select Sector) and XLC (Communication Select Sector) were excluded due to insufficient data availability.

To ensure an accurate comparison, this study uses measures of return (average daily return and daily upside deviation) and risk (daily downside deviation). These calculations yield average daily returns, upside risk, and downside risk over periods ranging from 3 to 24 years. Descriptive statistics of the data used are presented in Table 2.

XLK (0.058%) and XLE (0.044%) exhibit the highest daily average return, while XLP (0.030%) and XLU (0.030%) have the lowest mean daily return. In terms of average downside deviation, XLE (1.535%) and XLP (0.764%) are the most and least volatile, respectively. XLE (1.412%) shows the highest volatility in terms of upside deviation. Additionally, based on the return to volatility ratio, XLP (0.074%) is the best-performing ETF, while XLF (0.019%) is the worst. Except for XLE, all average daily return distributions exhibit positive skewness. Furthermore, all ETFs have a kurtosis value of less than 3, indicating a platykurtic distribution, characterized by shorter tails and a flatter peak than a normal distribution. This suggests fewer extreme values (outliers) than a normal distribution. Interpreting kurtosis in conjunction with other statistical measures and considering specific dataset characteristics is crucial for a comprehensive understanding of its distribution.

Table 2

Descriptive statistics for the data employed (3-year to 24-year average daily return, average daily upside deviation and average daily downside deviation from January 1, 1999 – December 31, 2022)

ETF	Avg. daily return (%)	Maximum avg. daily return		Minimum avg. daily return		Avg. upside deviation	Avg. downside deviation	Skewness	Kurtosis
		Return (%)	Year	Return (%)	Year				
XLK	0.058	0.086	4-year	0.028	23-year	1.079	1.171	-0.22	-0.71
XLE	0.038	0.089	3-year	0.018	15-year	1.412	1.535	1.77	3.01
XLU	0.030	0.040	4-year	0.021	15-year	0.909	0.971	0.06	-1.03
XLV	0.044	0.055	11-year	0.032	23-year	0.784	0.860	0.08	-1.51
XLI	0.039	0.055	4-year	0.030	24-year	0.962	1.081	0.67	-0.45
XLB	0.037	0.056	3-year	0.029	15-year	1.014	1.112	1.39	1.55
XLF	0.035	0.052	4-year	0.024	16-year	1.333	1.353	0.4	-1.37
XLP	0.030	0.045	4-year	0.022	24-year	0.676	0.764	0.73	0.96
XLY	0.041	0.060	4-year	0.022	3-year	0.955	1.131	0.09	0.7

Note: This table shows the descriptive statistics of the nine (9) SPDR sectoral ETFs sampled for the study. This consist of daily data span from 1st January 1999 to 31st December 2022. To ensure accurate comparison, a 3-year to 24-year average daily return, average daily upside deviation, average daily downside deviation was calculated for all the sector ETFs. *XLK* (0.058%) and *XLE* (0.044) have the highest daily average return, whereas *XLP* (0.030%) and *XLU* (0.030%) have the lowest mean daily return.

3. Empirical Results and Discussion

To come up with a robust inference of the comparative performance of sectoral ETFs, this section presents the ranking of the results from WRDDM where inefficiency scores are computed using different weights for risk (downside deviation) and return (upside deviation and daily average return). The nine different risk-return weight scenarios that are considered are as follows: ($w_x = 0.1, w_y = 0.9$), ($w_x = 0.2, w_y = 0.8$), ($w_x = 0.3, w_y = 0.7$), ($w_x = 0.4, w_y = 0.6$), ($w_x = 0.5, w_y = 0.5$), ($w_x = 0.6, w_y = 0.4$), ($w_x = 0.7, w_y = 0.3$), ($w_x = 0.8, w_y = 0.2$), and ($w_x = 0.9, w_y = 0.1$). These weights consider different investors ranging from extreme risk lover ($w_x = 0.9, w_y = 0.1$) to extreme risk averse ($w_x = 0.1, w_y = 0.9$).

By default, all inefficiency scores will be greater than or equal to zero, with higher scores indicating greater inefficiency in the sectoral ETF. The ETF achieving optimum performance will have a zero-inefficiency score. A higher inefficiency score suggests either low average daily return and/or upside deviation or high average daily downside deviation. According to the pooled 3-year to 24-year at various risk-return appetites, the top-performing ETFs are those positioned on the frontier with zero inefficiency scores, namely 11-year XLV (across all risk-return appetites), 14-year and 24-year XLF (across all risk-return appetites). This indicates that, the sectoral ETFs that lie on the frontier occur in the long run, a minimum of 11-year investment. A fully efficient ETF takes longer time period to yield a higher average daily returns and/or higher upside deviation.

We further investigate how the rankings change when different risk-return scenarios are assigned to w_x and w_y. The study periods are classified as short run (3-6year), medium run (7-10year) and long run (11-24year). Average inefficiency scores are calculated for each sectoral ETFs across various time horizon. Robust evidence suggests that performance rankings exhibit similar patterns across various risk-return appetites. However, some sectoral ETF rankings change, particularly in two extreme cases: when ($w_x = 0.1, w_y = 0.9$), and when ($w_x = 0.9, w_y = 0.1$).

The results in Table 3 shows the short run (3-6year) average inefficiency scores ranked in terms of their magnitude in the middle column, where 50% - 50% weights are assigned to risk and return ($w_x = 0.5, w_y = 0.5$). In Table 3 where ($w_x = 0.5, w_y = 0.5$), the top four performing sectoral ETFs in the short run are those with minimum average inefficiency score XLV (0.063), XLK (0.066), XLB (0.222), and XLP (0.249). By way of comparison, the worst four performing ETFs are XLY (0.503), XLE (0.305), XLF (0.295) and XLI (0.286). Now the next important question is what happens to the ranking at the two extreme cases in the short run period. Considering the extreme risk averse scenario ($w_x = 0.1, w_y = 0.9$), it is evidenced that the ranking of the best and worst performing sectors remains the same. On the other hand, the ranking on the extreme risk loving scenario ($w_x = 0.9, w_y = 0.1$) exhibited slight changes. The top four performing ETFs at the extreme risk loving scenario are XLV (0.041), XLK (0.042), XLU (0.082) and XLB (0.092). Conversely the worse four performing ETFs are XLY (0.209), XLF (0.182), XLI (0.121), and XLP (0.111). Interestingly, XLU and XLP were ranked among the best and worst performing sectoral ETFs respectively. Under risk-loving conditions, the utilities sector (XLU) demonstrates improved performance, indicating its potential appeal to investors with higher risk tolerance. Conversely, the consumer staples sector (XLP) is notable for its strong performance when risk and return are weighted equally. However, it performs poorly under high-risk conditions, suggesting it is less efficient in such scenarios.

Table 4 shows the medium term (7-10year) average inefficiency scores. The middle column shows the 50% - 50% weights assigned to risk and return ($w_x = 0.5, w_y = 0.5$). The top four best performing sectoral ETFs are XLK (0.051), XLV (0.075), XLF (0.181), XLI (0.210). Conversely, the worst four performing sectoral ETFs are XLE (0.653), XLY (0.257), XLU (0.253), and XLB (0.210). In the medium term, the ranking of the extreme risk averse scenario ($w_x = 0.1, w_y = 0.9$) remain same pattern. However, the ranking of the extreme risk loving scenario ($w_x = 0.9, w_y = 0.1$) changed slightly. The top four performing sectoral ETFs of the extreme risk loving scenario are XLK (0.044), XLV (0.047), XLF (0.081), and XLB (0.100). Conversely, the worst performing sectoral ETFs are XLY (0.173), XLE (0.141), XLI (0.117) and XLP (0.113).

Both the healthcare (XLV) and technology (XLK) sectors consistently demonstrate superior performance, highlighting their resilience and efficiency in both moderate and highly risk-averse conditions. These sectors are likely stable investment opportunities even when risk is a significant factor. In both balanced and risk-averse contexts, the energy sector (XLE) consistently underperforms, indicating its high volatility and inefficiency. Consequently, investors should exercise caution when considering energy sector ETFs for medium-term investments. The rankings in the extreme risk-loving scenario show slight variations, underscoring the importance of considering risk preferences. Sectors such as consumer discretionary (XLY) and utilities (XLU) demonstrate significant performance variability based on the investor's risk tolerance. The consumer staples sector (XLP) exhibits inefficiency in high-risk scenarios, as evidenced by its weak performance under extreme risk-loving conditions. This suggests that XLP may not be the optimal choice for risk-seeking investors in the medium term.

Table 3
Average Inefficiency scores for short run period (3-6year) at different risk (w_x) and return (w_y) appetite

Year	ETF	Avg. Inefficiency score $w_x = 0.1$ $w_y = 0.9$	Ranking	Avg. Inefficiency score $w_x = 0.5$ $w_y = 0.5$	Ranking	Avg. Inefficiency score $w_x = 0.9$ $w_y = 0.1$	Ranking
3-6year	XLK	0.118	2	0.066	2	0.042	2
	XLE	0.643	7	0.305	8	0.107	5
	XLU	0.468	5	0.260	5	0.082	3
	XLV	0.113	1	0.063	1	0.041	1
	XLI	0.515	6	0.286	6	0.121	7
	XLB	0.400	3	0.222	3	0.092	4
	XLF	1.06	9	0.295	7	0.182	8
	XLP	0.448	4	0.249	4	0.111	6
	XLY	0.904	8	0.503	9	0.209	9

Note: This table represents the ranking of the average inefficiency scores (in ascending order) of short run based on the middle column scores where 50-50% weights are assigned to ($w_x = 0.5, w_y = 0.5$). By design, all inefficiency scores will be greater or equal zero. the greater the score, the more inefficient the sectoral ETF.

Table 4
Average inefficiency score for the medium-term period (7-10years) at different risk (w_x) and return (w_y) appetite

Year	ETF	Avg. Inefficiency score $w_x = 0.1$ $w_y = 0.9$	Ranking	Avg. Inefficiency score $w_x = 0.5$ $w_y = 0.5$	Ranking	Avg. Inefficiency score $w_x = 0.9$ $w_y = 0.1$	Ranking
7-10year	XLK	0.091	1	0.051	1	0.044	1
	XLE	1.176	9	0.653	9	0.141	8
	XLU	0.457	7	0.253	7	0.104	5
	XLV	0.135	2	0.075	2	0.047	2
	XLI	0.378	4	0.210	4	0.117	7
	XLB	0.419	6	0.232	6	0.100	4
	XLF	0.325	3	0.181	3	0.081	3
	XLP	0.401	5	0.223	5	0.113	6
	XLY	0.463	8	0.257	8	0.173	9

Note: This table represents the ranking of the average inefficiency scores (in ascending order) of medium term based on the middle column scores where 50-50% weights are assigned to ($w_x = 0.5, w_y = 0.5$). By design, all inefficiency scores will be greater or equal zero. the greater the score, the more inefficient the sectoral ETF.

Table 5 below shows the long run (11-24year) average inefficiency scores. The middle column shows the 50% - 50% weights assigned to risk and return ($w_x = 0.5, w_y = 0.5$). According to Table 5 the top four performing sectoral ETFs are XLK (0.096), XLP (0.174), XLV (0.175) and XLY (0.194). On the other hand, the top worst performing ETFs are XLE (0.472), XLU (0.262), XLI (0.239) and XLB (0.238). Slight changes occur at the two extreme cases. For instance, the ranking of the top four performing sectoral ETFs at extreme risk averse scenario are XLV (0.157), XLK (0.172), XLP (0.314) and XLY (0.347). conversely, the four worse performing ETFs are XLE (0.839), XLB (0.517), XLU (0.465) and XLI (0.429). On the other hand, considering the extreme risk loving scenario, the top four performing ETFs are XLK (0.046), XLV (0.050), XLF (0.054), and XLU (0.088). In contrast, the worst four performing ETFs are XLE (0.123), XLY (0.113), XLB (0.105), and XLI (0.104).

The long run analysis reveals significant variability in the performance of sectoral ETFs under extreme risk scenarios. In the extreme risk-averse scenario, the health sector (XLV) exhibits the best performance, highlighting its stability during uncertain times. Conversely, in the extreme risk-loving scenario, the technology (XLK) and financial (XLF) sectors outperform, reflecting their high potential returns during aggressive investment strategies over the long run. The energy sector (XLE) consistently underperforms, underscoring its volatility and inefficiency in both risk-averse and risk-loving contexts. While the utility sector (XLU) performs poorly overall, it shows improved performance under the extreme risk-loving scenario, suggesting its potential attractiveness under specific risk preferences.

Table 5
Average inefficiency score for the long run period (11-24years) at different risk (w_x) and return (w_y) appetite

Year	ETF	Avg. Inefficiency score $w_x = 0.1$ $w_y = 0.9$	Ranking	Avg. Inefficiency score $w_x = 0.5$ $w_y = 0.5$	Ranking	Avg. Inefficiency score $w_x = 0.9$ $w_y = 0.1$	Ranking
11-24year	XLK	0.172	2	0.096	1	0.046	1
	XLE	0.839	9	0.472	9	0.123	9
	XLU	0.465	7	0.262	8	0.088	4
	XLV	0.157	1	0.175	3	0.050	2
	XLI	0.429	6	0.239	7	0.104	6
	XLB	0.517	8	0.238	6	0.105	7
	XLF	0.404	5	0.225	5	0.054	3
	XLP	0.314	3	0.174	2	0.096	5
	XLY	0.347	4	0.194	4	0.113	8

Note: This table represents the ranking of the average inefficiency scores (in ascending order) of medium term based on the middle column scores where 50-50% weights are assigned to ($w_x = 0.5, w_y = 0.5$). By design, all inefficiency scores will be greater or equal zero. the greater the score, the more inefficient the sectoral ETF.

4. Practical Implication and Investment Recommendations

The analysis consistently reveals that, regardless of the assigned weights to risk and returns, XLK and XLV emerge as the top-performing ETFs throughout the investment horizon. This indicates their attractiveness for investment across a spectrum of risk-return appetites, from extreme risk aversion to risk-loving investors, in both short, medium and long-term periods. The overall results clearly demonstrates that the technology and healthcare select sectors are the best-performing sectors in the stock market over all time horizons. This observation confirms the assertion by Valadkhani and Moradi-Motlagh (2023) that the technology and medical equipment industries have exhibited remarkable performance in the US equity market, thereby drawing significant investor focus to these sectors.

Within the technology select sector, recent rapid advancements in areas such as artificial intelligence, growth in cybersecurity, and the release of improved products from leading technology companies have driven increased investment. This has resulted in higher returns and upside deviations for the technology sector across all investment horizons, regardless of risk-return appetite. Technological products from XLK holdings, including Apple, Microsoft, Amazon, Alphabet, Tesla, and Johnson & Johnson, have achieved global reach in recent decades, attracting higher prices, returns, and upside deviations. Additionally, the global emphasis on digitization by various departments and agencies further enhances the technology sector's potential for commanding higher returns and upside deviations.

Regarding the healthcare sector, the aging population in many developed countries drives an increasing demand for healthcare services and products, thereby boosting the sector's performance. Furthermore, the inelastic demand for healthcare services and the growth of biotechnology within the sector significantly contribute to its robust performance.

In contrast, from the pooled results, the XLE sector, except the 3-year period, exhibits poor performance across the years regardless of the risk-return appetite. Several factors may account for these subpar performances. The volatility of oil and gas prices, influenced by the dynamics of the global demand and supply market, significantly impacts the energy sector. These price fluctuations underpin the increased downside risk of the energy sector. The energy sector is particularly susceptible to geopolitical risks, including changes in government policies, conflicts in oil-producing regions, and trade tensions, which can disrupt supply chains and affect profitability. The continuous growth of environmental, social, and governance (ESG) considerations has led many investors to shift their attention away from the traditional energy sector, negatively impacting its performance. The decline in the energy sector's prices can also be attributed to the decisions made by the Organization of the Petroleum Exporting Countries (OPEC). OPEC's decisions on production levels have a substantial influence on oil prices and, consequently, the overall success of the energy sector.

According to the pooled results, XLB is among the top four performing sectors in the short run, though its performance diminishes over the long term. Investors can capitalize on this by focusing their investments in the materials sector for shorter durations. Several factors contribute to the performance of the materials sector. The sector is highly sensitive to the economic cycle. During economic downturns, demand for materials such as chemicals, metals, and construction materials declines, adversely affecting the sector's long-term performance. This cyclical nature of the economy introduces high volatility and reduced stability over extended periods, sharply impacting the materials sector in the long run. Additionally, the performance of materials companies is closely correlated with the prices of basic materials and commodities, which are subject to significant volatility and influenced by global supply and demand dynamics.

Conversely, XLP and XLY consistently exhibit poor performance from the 3-year to the 12-year period. However, their performance improves from the 13-year to the 24-year time horizon. XLP, XLY, and XLF perform better in the long run but worse in the short run. Several factors contribute to the performance of these sectors. For instance, the consumer staples sector (XLP) comprises essential products such as food items, beverages, and household goods, which have inelastic demand regardless of economic conditions. This stability accounts for its long-term growth. The sector is also known for its defensive nature, providing reliable and less volatile returns, making it appealing to long-term investors. Consumer staples companies like Coca-Cola, Pepsi, Costco Wholesale, Walmart, and Procter & Gamble offer attractive dividends for reinvestment, which yield substantial long-term returns. On the other hand, the essential nature of consumer staples products limits opportunities for rapid growth, resulting in less impressive short-term returns. Since this sector is less dependent on overall economic performance due to its inelastic demand, it does not benefit significantly from short-term economic upswings.

Consumer discretionary sectors, on the other hand, experience strong long-term performance as consumer spending increases with economic growth. Goods such as automobiles, entertainment, and luxury items drive this sector's long-term success. However, in the short term, consumer discretionary stocks are more susceptible to economic fluctuations. During economic downturns, consumers tend to reduce their spending, negatively impacting this sector's performance. The financial sector (XLF) benefits significantly from long-term economic growth, which increases borrowing, investing, and the use of financial services.

XLI maintains a consistent ranking throughout the investment period, while XLB alternates between the 4th and 5th positions up to the 8-year mark. After this point, XLB displays poor performance until the 24-year mark.

For short-term investments, the Health Care (XLV) and Technology (XLK) sectors are highly recommended. Both sectors consistently rank at the top with the lowest inefficiency scores across different risk-return weights (risk averse, risk neutral and risk loving scenario). This indicates strong performance and efficiency, making them suitable for investors seeking stable returns in the short run. Conversely, sectors like Financials (XLF) and Consumer Discretionary (XLY) exhibit higher inefficiency scores, suggesting greater volatility and potential inefficiency irrespective of the risk-return scenario. These sectors should be approached with caution in the short term.

In the medium term, Technology (XLK) continues to be a top performer, maintaining the highest efficiency across all risk-return scenarios. Health Care (XLV) also remains a strong candidate, ranking second consistently. Investors with a medium-term horizon should consider these sectors for their portfolios. Additionally, Utilities (XLU) and Financials (XLF) show moderate inefficiency scores, making them viable options for diversification. However, Energy (XLE) and Consumer Discretionary (XLY) sectors exhibit high inefficiency scores, indicating they may be less suitable for medium-term investments.

For long-term investments, Technology (XLK) and Health Care (XLV) remain the most efficient sectors, consistently ranking at the top. These sectors are ideal for long-term investors seeking growth and stability. Utilities (XLU) and Financials (XLF) also perform relatively well, making them good options for long-term diversification. On the other hand, Energy (XLE) and Consumer Discretionary (XLY) continue to show higher inefficiency scores, suggesting they may be less reliable for long-term investments.

A diversified portfolio should include a mix of defensive, growth-oriented, and cyclical sectors to balance risk and return. By combining the stability of XLV and XLK with the moderate efficiency of XLU and XLF, investors can create a robust investment strategy.

Diversification helps mitigate the impact of market volatility and enhances the potential for long-term growth.

Investors should adjust their sector allocations based on historical performance and current market conditions. For example, during periods of economic uncertainty, increasing exposure to defensive sectors like XLV and XLK can provide stability. Conversely, during economic recoveries, shifting towards cyclical sectors such as XLF and XLI can capture growth opportunities. Regular monitoring and rebalancing of the portfolio are essential to maintain the desired risk-return profile. Investors should periodically review the performance of their sector allocations and make adjustments as needed to align with their investment goals and market outlook. This proactive approach ensures that the portfolio remains resilient and responsive to changing market dynamics.

By following these investment recommendations, investors can strategically navigate market fluctuations and enhance their potential for achieving long-term financial objectives. This comprehensive approach to sector allocation, grounded in inefficiency score analysis, provides a solid foundation for building resilient and growth-oriented investment portfolios.

5. Summary and Conclusion

This study assesses the performance of US-based sectoral ETFs using a non-parametric model derived from the WRDDM, which allows for the consideration of varying risk-return appetites. The model not only aims to maximize returns and minimize risk but also accommodates different risk-return preferences by assigning extreme weights to risk and return at different time horizons. Regardless of the risk-return appetite, the study identifies three efficient sectoral ETFs (11-year XLV, 14-year XLF, and 24-year XLF).

Consistently, XLK and XLV emerge as the top-performing ETFs across all investment horizons (3-year to 24-year), irrespective of risk-return preferences. Conversely, XLE consistently ranks as the least performing ETF regardless of the sampling period. Between the 3-year and 12-year periods, XLP and XLY exhibit poor performance, but they improve between the 13-year and 24-year periods.

Moreover, XLU, XLI, XLB, XLF, and XLP show significant changes in rankings with an increase in weight differentials. For instance, XLU and XLF perform worse as more weight is assigned to risk than returns. Conversely, XLI, XLB, and XLF perform better as more weight is assigned to returns than risk. Additionally, regardless of the risk-return scenario, XLU, XLV, XLI, XLF, XLP, and XLV achieve their lowest inefficiency scores in the long run.

5.1 Practical Implications for Institutional Investors and Retail Investors

Institutional investors, given their long-term financial commitments and strategic investment approaches, may find it advantageous to allocate more resources to XLK and XLV to capitalize on sustained growth opportunities. Meanwhile, retail investors, who often follow institutional trends or adopt passive investment strategies, can use this insight to prioritize these ETFs for reliable returns. The performance of sector-specific ETFs is significant for both groups, with XLK (Technology) and XLV (Health Care) consistently outperforming across various time frames. This consistency underscores their importance as essential components in well-diversified and long-term portfolios. Conversely, despite their strong long-term performance, XLP (Consumer Staples) and XLY (Consumer Discretionary) experienced short-term underperformance, suggesting that these sectors may be more appropriate for investors with a long-term perspective who are willing to endure temporary fluctuations for future gains. Additionally, XLB (Materials) initially showed strong results but saw its momentum decline over time, making it a compelling option for short-term investment strategies that aim to capitalize on early strength before performance tapers off.

5.2 Practical Implication for Portfolio Managers and Hedge Funds

Hedge funds and portfolio managers, often driven by performance-based objectives and attuned to changing market dynamics, can leverage these sector trends to craft strategic asset allocation and sector rotation strategies. The consistent long-term strength of XLK (Technology) and XLV (Health Care) suggests that maintaining or increasing exposure to these ETFs could enhance portfolio stability and support sustained growth over time. XLB (Materials) may be more suitable for short-term, high-risk investment strategies, as it demonstrates strong initial performance but struggles to maintain momentum over extended periods. Furthermore, the delayed recovery of XLP (Consumer Staples), XLY (Consumer Discretionary), and XLF (Financials) presents potential opportunities for timing-based investment approaches, including mean-reversion and contrarian strategies. Hedge funds can capitalize on these sector-specific inefficiencies by employing leverage and derivatives to enhance alpha generation, exploiting market overreactions to temporary underperformance.

5.3 Practical Implications for Market Traders and High Frequency Traders

The long-term performance patterns of sectoral ETFs offer valuable indirect insights for HFTs, and market participants focused on short-term dynamics. Although HFTs and short-term traders primarily concentrate on intraday volatility and microstructure movements, awareness of institutional and portfolio managers' tendency to rebalance toward outperforming sectors such as XLK (Technology) and XLV (Health Care) can serve as a predictive signal for volume fluctuations and short-term price shifts. Additionally, algorithmic traders may capitalize on the price swings driven by XLB's (Materials) brief initial outperformance followed by subsequent declines. To further enhance execution efficiency and profitability, HFTs can develop event-driven strategies that exploit periodic portfolio rebalancing activities—such as quarterly or annual adjustments—that reallocate capital from underperforming sectors to those demonstrating sustained strength.

5.4 Practical Implications for Financial and Media Analysts

Financial media sources and market analysts play a crucial role in shaping investor sentiment and broader market narratives. While the performance of sectors such as XLP (Consumer Staples) and XLY (Consumer Discretionary) varies depending on the investment horizon, requiring nuanced and context-driven analysis, the consistent long-term strength of XLK (Technology) and XLV (Health Care) provides a foundation for persistently optimistic sector outlooks. Short-term underperformance in consumer-related industries may initially prompt reactionary reporting, but a more balanced perspective that highlights their long-term potential could emerge over time. Analysts can leverage these sector trends to guide investor expectations and offer well-informed recommendations that align with long-term investment strategies. By incorporating these insights into their reports and commentary, financial media and research institutions can provide comprehensive, timely guidance that supports both short-term tactical decisions and broader strategic planning.

5.5 Practical Implication for Regulatory Bodies and Federal Reserves

Sector-specific ETF trends can serve as valuable indicators for the Federal Reserve and other monetary authorities in assessing financial stability and broader economic conditions. The short-term underperformance of consumer-related sectors, such as XLP (Consumer Staples) and XLY (Consumer Discretionary), may reflect underlying weaknesses in consumer spending, suggesting the potential need for policy measures aimed at supporting household income or stimulating demand. In contrast, the sustained strength of the health care (XLV) and technology (XLK) sectors may signal ongoing structural shifts in the economy, including demographic changes such as an aging population and the accelerating impact of digital transformation, which could shape research funding priorities and industrial policy. Additionally, the concentration of institutional investments in persistently outperforming sectors like XLK raises concerns about systemic risk, potentially warranting regulatory scrutiny of portfolio diversification strategies to mitigate financial vulnerabilities.

5.6 Practical Implications for Exchange Operations (NYSE, Nasdaq, CBOE)

The operational strategies of stock exchanges such as the NYSE, Nasdaq, and CBOE are directly influenced by sectoral ETF performance trends. To meet investor demand and encourage trading activity, exchanges may prioritize the development and promotion of financial instruments tied to consistently strong-performing sectors, including leveraged and inverse ETFs based on XLK (Technology) and XLV (Health Care). Additionally, anticipated short-term sector movements, such as the initial strength of XLB (Materials), can inform the timing and marketing of sector-based index futures or thematic trading platforms. By forecasting increased trading volumes in outperforming ETFs, exchanges can refine price discovery mechanisms, enhance market-making strategies, and optimize liquidity management to support efficient market operations.

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