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The Evolution of the Retail Investor- A Technical Analysis Approach

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Abstract

This paper focuses on the evolution of technical analysis over the course of the last 17 years, evaluating the correlation of such progress with the ascension in retail investing, given the development of the online brokerage industry during this period. In a first stage, a market study is performed to understand the growing magnitude of retail investing. In a second stage, technical indicators are evaluated for two distinct asset classes, with the purpose of understanding how the efficacy of signals generated by technical trading rules evolves, according to asset type. In a last stage, results are combined to determine if the evolutionary process on both metrics is related. We find a significant relation between the evolution in retail investing and the one of technical trading efficacy for technology stocks. We further find an increasing propensity for technical analysis to correctly predict price moves for small-cap ETFs, although the explanatory power of the evolution in retail investing is not significant in explaining such increase.

Keywords: Retail investing, Online brokerage, Technical analysis, Efficient market hypothesis, Stock market anomalies, Technology Stocks, Small-Cap index ETFs, Large-Cap index ETFs

1. Introduction

Technical analysis has been widely present in financial practice since its popularization in the 1930s, following the work of Charles Dow on this theme in 1884. It relies in the use of past price and volume information to forecast future price behavior. Pring (2002) describes it as "the idea that prices move in trends that are determined by the changing attitudes of investors towards a variety of economic, monetary, political, and psychological forces". Despite an associated level of skepticism among academic critics, several market studies indicate that technical analysis has been commonly employed by finance professionals among several financial institutions.

During the last two decades, the emergence of the internet, fostered by fast computerization, motivated a rapid breakthrough in online investing, erasing the gap in financial information between professional and retail investors, that prevailed in the pre-internet era. Monetary policies implemented in the wake of the global financial crisis contributed to a lower attractiveness in fixed income assets, steering investors towards equities. Withal, a low transaction cost environment spawned amidst rising competition in the brokerage industry. This sequence of events, allied with the recent emergence of zero-fee online brokers, as *Robinhood*, and of automatized technical trading platforms popular among retail investors, as *TradingView* and *Metatrader 4*, revolutionized the way investing is perceived. As JPMorgan recently acknowledged (Cheng (2017)), ”Fundamental discretionary traders account for about 10% of trading volume in stocks today" and "the majority of investors today don't buy or sell stocks based on stock specific fundamentals.".

Under this corollary, the present study intends to assess the progress of some of the most popular technical trading indicators, over time, further evaluating its relation to the rise of the retail investor and trying to assess if technical analysis emulates a self-fulfilling prophecy. This paper is organized as follows: section 2 reviews the related literature; section 3 describes the used methodology; section 4 discusses the obtained results and section 5 presents the main conclusions.

2. Literature review

2.1. Technical Analysis

The widespread adoption of technical analysis (henceforth TA) in financial markets and the comprehensive volume of academic papers dealing with this subject present robust evidence of its relevance at both the professional and the academic levels.

TA originally dates from Charles H. Dow, in 1884, who first documented observable security price patterns in the U.S. market. This idea was subsequently popularized by Rhea (1933), during the decade of 1930, followed by several studies on the topic. Merton (1948) introduced a possible explanation for trends observed in price charts, concluding that TA may perform as a self-fulfilling prophecy when a large group of investors follow its signals, conjunctly.

Given its rising popularity, diverse market surveys were conducted in this matter. Smidt (1965) and Brorsen and Irwin (1987), who surveyed amateur traders and public fund's advisory groups, respectively, identified that more than half of the respondents, regardless of expertise, admittedly used chart analysis to identify trends. The Group of Thirty (1985), Frankel and Froot (1987), Taylor and Allen (1992) and Menkhoff (1997) performed surveys regarding the use of TA among investment professionals in large institutions, worldwide, finding that about 90% of the respondents relied on TA to identify trends and form expectations regarding future market pricing. Lui and Mole (1998), Cheung and Wong (2000) and Cheung and Chinn (2001) interviewed foreign-exchange dealers in the U.K. and in China, finding that approximately 30% of the respondents considered TA as the most important factor over short-term horizons. Oberlechner (2001) achieved similar conclusions on a study in several European foreign exchange markets, adding that the importance of TA within the industry exhibited signs of progression, over time.

Despite recognition among practitioners, academics tend to show some skepticism towards TA. Samuelson (1965) argued that, in efficient markets, it is neither possible to exploit currently available information to generate profits nor to extrapolate past pricing information to predict future prices. The introduction of the Efficient Market Hypothesis, by Fama (1970), further came to support the idea that markets are “informationally efficient”. Nevertheless, during the following decades, several studies emerged as endeavors to disapprove this theory. A behavioral model introduced by Summers (1986) states that “evidence found in many studies that the efficiency hypothesis cannot be rejected should not lead us to conclude that market prices represent rational assessments of fundamental valuations.”. Jegadeesh and Titman (1993; 2001) introduced the “momentum” factor, currently known as one of the most persevering market anomalies, that proved to generate significant returns over short-term periods. Chui et al (2010), Fama and French (1998; 2012) and Asness et al. (2013) further verified this anomaly.

Several theoretical explanations were also developed for the widespread use of TA. Some researchers endorsed TA as a valuable tool to predict price movements (Brock et al. 1992) or to add value to the investment process Lo et al. (2000), supporting their findings with empirical evidence in TA. Some studies reported profitable returns on moving average rules (Levich and Thomas (1991) and LeBaron, Arthur, and Palmer (1999)) and in pricing asymmetries (Osler et al. 2002). Schmidt (2002) and Slezak (2003) found that technical traders may succeed when capable of affecting market liquidity. Moskowitz and Grinblatt (1999), Chordia and Shivakumar (2002) and Hou (2007) demonstrated that industry affiliation allows to take advantage of higher correlations in stock returns, exploiting momentum. Lo and MacKinlay (1988) and Hong, Lim, and Stein (2000) verified that momentum strategies are more successful for small cap stocks. Ready (2002), Qi and Wu (2006), Hsu et al. (2009) and Shynkevich (2012) concluded that market maturity influences the predictability of TA as smaller markets are more prone to arbitrage opportunities. P. H. Hsu and Kuan (2005) found evidence in TA’s efficacy, when applied to small-cap indexes (as the Russel 2000), but not in large-cap ones (as the S&P500, the DJIA and the NASDAQ 100).

More recently, several studies emerged on the formulation and evaluation of technical trading models based on different operational tools (genetic programming, standard studies, model-based bootstrap, reality check and chart patterns), applied to different asset classes (equities, commodities, and currencies) for both advanced and emerging economies. Despite positive findings for most studies ((Creamer and Freund 2010, Gorgulho, Neves, and Horta 2011, Creamer 2012, N. Taylor (2014) and Berutich et al. (2016)) there is no consensus on the evolution of TA due to imprecise profitability results, commonly linked to erroneous risk measurement and transaction costs estimation. Given the large volume of studies on TA's profitability, we will rather concentrate on how TA's efficacy has evolved amidst the rising popularity of online investing.

2.2. Retail Investor Behavior

The retail investor (hereafter, RI) behavior, its market impact and its main drivers have been a widely discussed topic. In a survey study, Stewart (1949) concluded that amateur speculators traded against price reversals. This contrarian behavior was similarly reported by Barber and Odean (2000) and Schmitz and Weber (2012). Kumar and Lee (2006) have found that RIs' actions occur in group, given sentiment, with some stocks revealing high retail concentration levels. Ofek and Richardson (2005) found that the technology sector attracts more RIs rather than institutional interest. Barber, Odean, and Zhu (2008) additionally found that RIs significantly affect stock prices, in the short-term, inducing subsequent price reversals. Barber et al. (2005) and Engelberg et al. (2009) also concluded that news and the media have a considerable influence in RIs.

Daniel et al. (1998) reported overconfidence as an important factor to explain RIs' behavior. Fritz and Weinhardt (2016) argued that overconfidence may lead to a higher popularity of TA's methods and that automated TA systems, popular among RI communities, may induce collective behavior. Entertainment and gambling was also identified as a factor driving RIs behavior, according to Schmitz and Weber (2012), Schroff and Meyer (2013) and Meyer et al. (2014).

3. Methodology

3.1. Online Brokerage Data

Online brokerage data was extracted from the annual reports of the largest public online brokers[1] in both the United States (U.S.) and Europe, provided that it was accessible from 2006 onwards. In the U.S., four online brokers were found to satisfy the formerly mentioned characteristics: *Charles Schwab*, *E-Trade*, *Interactive Brokers* and *TD Ameritrade*. In Europe, only *Swiss Quote* complied. To extract data on RI's evolution, daily average transactions[2] (henceforth, DATs) were extracted, for each broker, relying on the important assumption that this industry's common metric may be used as a proxy to evaluate the presence of RIs in the market, since it represents the average number of transactions made, per day, during a given period. DATs were extracted in annual terms, the lower time frame available, and then averaged and aggregated into three-year periods.

To evaluate TA's performance over time, both individual stocks and indexes were selected, with the purpose of understanding how TA may differ within these two distinct asset types, according to idiosyncratic risk exposure, as suggested by Shynkevich (2012). Considering that indexes are not directly transactable, index–ETFs were considered. Our selection comprises three large-cap index ETFs- SPDR Dow Jones Industrial Average ETF (DIA), SPDR S&P500 ETF (SPY), and Invesco NASDAQ 100 ETF (QQQ); and two small-cap index ETFs- iShares S&P 600 small-cap ETF (IJR) and iShares Russel 2000 ETF (IWM). The purpose of testing indexes with different market capitalizations is to understand how TA has evolved relatively to market maturity, as evidenced by Ready (2002), or by P. H. Hsu and Kuan (2005). Selected stocks comprise the five most actively traded companies in the NASDAQ composite, measured by volume, from 2003 until

[1] According to www.investopedia.com and www.stockbrokers.com
[2] Formerly known as DARTs (Daily Average Revenue Trades), adjusted for zero commission trading.

2020[3]: Apple Inc. (AAPL), Microsoft Corp. (MSFT), Intel Corp. (INTC), Cisco Systems Inc. (CSCO) and Comcast Corp. (CMCSA) which, interestingly, all belong to the technology sector.

3.2. Technical Rules Employed

As technical indicators, three main groups were considered: Trend-following– Normal Moving Average (henceforth, MA); Oscillators – Moving Average Convergence Divergence (henceforth, MACD), Relative Strength Index (henceforth, RSI) and Slow Stochastic (henceforth, SS); Patterns– Support and Resistance (henceforth, S&R) and Fibonacci Retracements.

MAs are a trend following indicator commonly used to identify price trends. This indicator is given by the average price, over the last T days, computed on a rollover basis. For the purpose of this study, T is considered for 5, 10, 20, 50, 100 and 200 days[4]. It is defined as follows:

$$MA_t(T) = \frac{\sum_t^T Pt}{T}, \ (1)$$

where t is the considered period and P_t is the close price verified in t. According to Murphy, 1999, a buy (sell) signal is generated when the price crosses above (below) the MA line.

The MACD (Murphy 1999) is an oscillator obtained from the use of exponential moving averages (henceforth, EMAs). An EMA is defined as:

$$EMA_t(T) = EMA_{t-1}(T) \times \left(1 - \frac{2}{T+1}\right) + P_t \times \frac{2}{T+1}, \ (2)$$

where t is the considered period, P_t is the close price verified in t and T is the selected moving average period. The MACD strategy uses two EMAs: the 12 and the 26 period. The difference on these EMAs is computed, for every period, thus obtaining the MACD line. This line is then compared to a 9-period EMA of the MACD line, known as the signal-line. The difference between the MACD line and the signal-line is used to build a histogram, to understand price/trend evolution.

[3] Source: Bloomberg

[4] The most common periods, as suggested by Lim (2016), "Seven main components of moving averages", 449–451.

A widening (narrowing) histogram usually indicates that the trend is strengthening (weakening). Narrowing histograms always precede crossover signals, as indicated by Lim (2016). Accordingly, the strategy consists as follows: when the histogram starts narrowing and the MACD line crosses above (below) the signal-line, a buy (sell) signal is generated, considering the confirmation filter[5].

The RSI (Murphy 1999) is a commonly used momentum oscillator that compares the strength between recent gains and losses, determining overbought/oversold conditions. It defines as follows:

$$RSI_t(n) = 100 - \frac{100}{1+RS(T)}, \text{ with } RS(n) = \frac{Average\ Gains\ (T)}{Average\ Losses\ (T)}, \quad (3)$$

where *t* defines the considered period and RS(T) the average gains/losses over the last T periods, where T equates 9 or 14, usually. As suggested by Murphy (1999)[6], a 14-day period T was selected. The RSI will generate a signal comprehended between 0% and 100%. The strategy relies on two important levels: 30% and 70%. When the RSI crosses 70%, from above to below (30%, from below to above), an overbought (oversold) condition verifies and, thus, a sell (buy) signal is formed, considering the confirmation filter.

The SS oscillator (Murphy 1999) is another common TA indicator. Three lines are used in the process: stochastics (%K), fast stochastics (%D) and slow stochastics (%Dn). %K is defined as:

$$\%K = 100 \times \frac{P_t - L(T)}{H(T) - L(T)}, \quad (4)$$

where P_t is the closing price on period *t*, and H(T) and L(T) are the respective highs and lows from the last T-periods. %D, known as *fast-stochastics*, is obtained as a 3-period MA of %K. By taking a second 3-period MA on %D, a smoother line commonly referred to as *slow-stochastics*, or %Dn, is obtained. In coherence with the RSI rule, T is commonly set to either 9 or 14 days. As suggested

[5] For oscillators (RSI and SS), a confirmation filter of 2 days is applied before the signal's formation, as suggested by both Murphy (1999)- "Filters- The two-day penetration rule", 122; and by Lo et al. (2000).
[6] Murphy (1999)- "The Relative Strength Index (RSI)", 240

by Murphy (1999)[7], a 14-day period was selected. Stochastics' levels rely between 0% and 100% and, similarly to the RSI, these indicate oversold/overbought conditions, relative to the last T-periods. The strategy relies on two important levels: 20 and 80. It works as follows: when %D crosses 80, from above to below (20, from below to above), an overbought (oversold) condition verifies and, thus, a sell (buy) signal is generated, considering the confirmation filter.

S&Rs were one of first patterns to be observed by Dow (1884) and are one of the simplest forms of TA. These levels are formed by recent maximum and minimum prices referred to as resistance and support levels, respectively. In order to design a method to automatically identify S&R levels, over time, two trends were computed: a 5-day (short-term) trend and a 200-day (long-term) trend. The process works as follows: when the slope of the short-term trend is positive (negative), the maximum (minimum) price obtained during that trend is extracted. If the slope of the long-term trend is positive (negative) and the maximum (minimum) price extracted is larger (smaller) than the previous registered resistance (support), the extracted price is updated as a new resistance (support). Otherwise, if the slope of the long-term trend is negative (positive), the maximum (minimum) price extracted from the short-term trend is always updated as a resistance (support). Posteriorly, whenever the daily closing price closes near the most recent support/resistance (considering a 1% margin), it is validated and accounted for respecting the support/resistance. The evolution on this counting is then computed, on an annual basis, to understand if S&R levels have evolved as "friction" zones, over time. To evaluate the indicator's efficacy, a breakout strategy is considered: whenever the price breaks a resistance (support) level, a buy (sell) signal is generated[8].

Fibonacci retracements (Lim 2016) are a common behaviorally-driven indicator that rely on the fact that, during strong bullish (bearish) trends, prices occasionally retract from the recent peak

[7] Murphy (1999)- "Stochastics (K%D)", 246

[8] For a better understanding of the strategy, consider Figure 1 on the appendix.

(trough), opposed to the main trend, to a support (resistance) level defined by Fibonacci ratios[9]. Those retractions are commonly used as possible entry points during the course of the trend. Therefore, after a Fibonacci retracement has been verified, the price is expected to return back to the main trend. Due to the complexity of this indicator, a single leg[10] retracement was considered, for each period, implying that retracements do not accumulate. A length period of 20 trading days was used to identify retracements. Price trends are identified using a 5-day trend line. As prices retract closely, but not exactly, to Fibonacci levels, a 2.5% margin[11] was considered for each level, creating thus Fibonacci retracement zones. The strategy is defined as follows: during a positive (negative) trend, when price retracts, at most, to one retracement zone, a buy (sell) signal is formed.

For each indicator applied, on each equity product, two parameters were determined: average efficacy and average return. The former evaluates how frequently, on average, the strategy correctly predicted price movements. The latter is computed as the average return obtained, provided that the strategy was successful, aiming to evaluate how returns from successful trades evolved over time. Both parameters are measured through the course of five trading days (referred to as K, for K=1 to 5) following the signal's formation, to assess the subsistence of the TA's signals over a 5-day short horizon. For each parameter, data on all indicators is then aggregated, using an equally weighted average, and subsequently organized by asset class. Thereafter, the evolution of each parameter is subject to a time-series analysis, assessing thus the robustness of the trend, throughout time. Following that, a Pearson correlation test and an autocorrelation test were computed. Lastly, the evolution of parameters is grouped in three-year periods and then compared to the one obtained for DATs, over the same time span.

[9] The usual Fibonacci retraction levels are 23.6, 38.2, 50, 61.8 and 78.6, as described by Lim (2016)- "Fibonacci Based Ratio Intervals", 370

[10] As described in Lim (2016)- "Fibonacci Two-Leg Retracement Formations", 402

[11] As suggested by Lim (2016)- "Fibonacci, Dow, Gann, and Floor Trader's Pivot Point Levels", 397-400

4. Discussion of Results

4.1. Online Brokerage Data

Given the scope of this study, our expectation is that an increasing presence of RIs in the market should be observable through an increase in both the number of accounts and in DATs.

Period	Total Equity ($B)	Number of Accounts (Ths)	DATs (Ths)
[2006 - 2008]	$1,745	14,635	325.5
[2009 - 2011]	$2,099	16,561	383.1
[2012 - 2014]	$3,089	18,580	412.4
[2015 - 2017]	$4,178	23,134	507.6
[2018 - 2020]	$6,084	31,545	732.5
CAGR %	*8.68%*	*5.25%*	*5.56%*

Table 1- Aggregated evolution of evaluated metrics, for online brokers

As we can verify in Table 1, overall equity held by online brokers has pronouncedly increased during the period under analysis, in conjunction with the number of brokerage accounts. The CAGR for the overall equity held is higher, comparatively to the one for the number of accounts, thus suggesting that average equity per brokerage account has also increased, on average, over time. Given that equities are the main asset class transacted by all the brokers in the analysis, these results may therefore support that there has been a higher tendency to allocate investments towards equities. Similarly, DATs also form an increasing trend, over time. The fact that CAGR for DATs is slightly higher than the one obtained for the number of accounts not only suggests that an increase in the number of accounts relates to a higher volume of transactions in the market, but it further indicates that DATs per account have marginally increased over time, on average. Thus, it seems that the average investor is transacting more often, as initially expected, as investments over shorter-time horizons are more commonly employed by technical analysts, comparatively to fundamental investors who rather focus on longer-term strategies.

4.2. Technical Indicators

4.2.1. Efficacy and Returns in Individual Stocks

In Table 2, aggregated efficacy on the technical rules studied exhibits a positive trend pattern, over time, for the periods under analysis.

		K = 1	K = 2	K = 3	K = 4	K = 5
Period	[2003 - 2005]	49.3%	47.0%	47.4%	48.4%	46.8%
	[2006 - 2008]	50.5%	46.5%	46.8%	48.3%	47.1%
	[2009 - 2011]	50.1%	51.4%	49.5%	48.0%	50.4%
	[2012 - 2014]	51.3%	52.6%	51.3%	50.1%	51.2%
	[2015 - 2017]	51.9%	53.4%	52.5%	52.3%	54.7%
	[2018 - 2020]	57.1%	55.1%	55.6%	53.6%	53.9%
	Average Efficacy	51.7%	51.0%	50.5%	50.1%	50.7%
	CAGR	0.63%	0.57%	0.44%	0.27%	0.30%

Table 2- Aggregated evolution of indicators' efficacy for individual stocks

Despite a decrease during the 2006-2008 period, efficacy in indicators improved constantly throughout the periods, since then. Overall, aggregated efficacy has grown at a positive CAGR for all levels of K. Howbeit, this metric lessens as K increases, indicating thus that the evolutionary process of TA seems to be more obvious in the very short-term, particularly in the day following the formation of signals (K = 1). Additionally, this idea is verified through a partial decline in average efficacy over the continuation of K. A plausible premise to justify this corollary may be that signals tend to lose some efficacy over time, as other factors start outweighing the price behavior. Results therefore support that the sooner the investor follows the indicator's guideline, the more likely he or she is to capture a price movement in favor of signal's recommendation. Regardless, the reduction in efficacy over K is not that relevant once, on the fifth day after the signal's formation, average efficacy is still approximately 51%, accounting therefore for a reduction in efficacy of about 1% over the course of five days.

An evaluation of the decline in efficacy throughout K was further performed to measure how this metric evolved under the periods analyzed[12]. However, no trend was observed, allowing to conclude that the rate at which TA's efficacy decreases, over K, has not significantly changed.

From Table 3 it is possible to infer that the positive evolution on the aggregated efficacy for TA indicators is highly significant (using a 97.5% confidence interval) for all levels of K, rejecting thus the hypothesis of the verified trend being a product of random fluctuations, over time.

		K = 1	K = 2	K = 3	K = 4	K = 5
Signal's Performance	Slope	0.0042	0.0056	0.0056	0.0037	0.0055
	Pearson R	69.5%	76.2%	75.3%	59.4%	72.5%
	t-statistic	3.864	4.711	4.574	2.954	4.209
	P-Value	0.0687%	0.0118%	0.0156%	0.4663%	0.0333%

Table 3- Time-series statistical analysis on average efficacy obtained in TA, for individual stocks

These results are, in fact, satisfactory and complement those from Table 2, supporting the idea that signals generated from TA strategies have progressively become more efficient in correctly predicting price moves for individual stocks, throughout the periods analyzed. The robustness of this trend is further supported by a clear pattern of positive autocorrelations from lags 1 through 5, as shown in Table 4, indicating serial dependence on TA's efficacy throughout the periods.

		K = 1	K = 2	K = 3	K = 4	K = 5
Lagging Period (Days)	1	44.5%	47.9%	52.2%	39.4%	54.6%
	2	31.5%	33.9%	32.2%	26.6%	33.6%
	3	10.8%	37.7%	26.6%	3.9%	17.2%
	4	1.1%	17.5%	28.9%	23.1%	21.8%
	5	11.4%	23.4%	20.5%	0.6%	6.7%
	6	-1.8%	-3.6%	-6.2%	-7.8%	-2.3%

Table 4- Autocorrelation analysis on the efficacy levels obtained, year over year

[12] Table II from the appendix

Despite a significant linear trend over time, for all levels of K, as suggested from Tables 3 and 4, it is interesting to observe that there are some irregular observations throughout the progress of efficacy, when considering annual data[13]. Concretely, it is possible to observe two major reductions in TA's efficacy, throughout time. The first occurs in 2007, a period characterized by severe market stress attributable to the global financial crisis during which TA's efficacy was reduced by approximately 10.3%, explaining thus the lower results obtained in the 2006-2008 period, in Table 1. The second is observable in 2020, during which TA's efficacy was reduced by roughly 9.8%, in the wake of the pandemic crisis during that year, which negatively affected the stock market. Based on these similar one-off events, it seems that TA's efficacy is negatively affected during abnormal stock market volatility periods. Measured efficacy levels recovered right after these exceptional periods and reveal a significantly linear evolution, over time.

To understand how the evolutionary progress of TA relates to the one of the RI, a statistical significance test was performed on the correlation of the development of DATs with the progress of TA's efficacy for the chosen individual stocks, over time. Results are shown in Table 5.

		K = 1	K = 2	K = 3	K = 4	K = 5
DATs	Pearson R	80.9%	58.0%	57.0%	42.6%	39.5%
	R Squared	65.4%	33.6%	32.5%	18.2%	15.6%
	t-stat	4.955	2.566	2.500	1.699	1.551
	P-Value	0.0131%	1.1740%	1.3306%	5.6550%	7.2476%

Table 5- Significance test on the relation between DATs and TA's Efficacy in Individual Stocks

Data reveals a remarkable degree of significance on the correlation between both metrics for the periods under analysis. This evidence may relate to the suggestion made by Ofek and Richardson (2005) that RIs are more attracted to technology related stocks, rather than institutional investors,

[13] Table II from the appendix

which might explain the increasing efficacy in TA for this type of stocks, given the cornerstone assumption of this study that the growth in DATs is a good proxy for the rise of RI's activity. This idea is exceptionally important as stocks comprised in this study directly relate to the technological sector. The R-Squared measure exhibits a decreasing trend on the days following the formation of the TA strategy's signal. For K = 1, the evolution in DATs is capable of explaining considerably 65% of the variance verified on the evolution of TA's efficacy. Nevertheless, this explanatory power fades for each incremental unit of K. An obvious rationale for this phenomenon follows the previous reasoning that, over time, other non-identified factors progressively predominate over the RI effect, on individual stock prices. The same conclusion can be withdrawn from the P-Value results which demonstrate a decrease in significance as days following signal's formation elapse. Nevertheless, the relation between DATs and TA exhibits a continuous degree of significance up to the third day following signal's formation, considering a 95% confidence interval, which allows us to conclude that the verified annual progress of RIs has been significantly related to the annual evolution of TA indicators, up until K = 3. Furthermore, it is also possible to infer that these results add support to the previously made conclusion that the sooner the technical analyst acts on the formed TA signals, the more likely he or she will be to capture a price move that favors the strategy.

Table 6 presents data on the evolution of TA returns, when signals were efficient.

		K = 1	K = 2	K = 3	K = 4	K = 5
Period	[2003 - 2005]	1.1%	1.6%	2.2%	2.3%	2.6%
	[2006 - 2008]	1.5%	2.0%	2.6%	2.9%	3.3%
	[2009 - 2011]	1.3%	1.8%	2.2%	2.5%	2.8%
	[2012 - 2014]	1.0%	1.3%	1.8%	2.0%	2.3%
	[2015 - 2017]	0.9%	1.3%	1.6%	1.9%	2.0%
	[2018 - 2020]	1.6%	2.1%	2.6%	3.1%	3.2%
	Average Return	1.2%	1.7%	2.2%	2.4%	2.7%

Table 6- Evolution of returns, over time, for efficient signals on Individual Stocks

Along with the positive and significant evolution in both DATs and TA's efficacy, one could additionally expect that returns on successful TA strategies exhibited similar signs of progress. However, from the data presented in Table 6, it is possible to conclude that this idea does not materialize. Despite a considerable increase in return levels for the 2018-2020 period, there seems to exist no steady or significant progress over time. The punctual results obtained during the last studied period are primarily driven by 2020 observations[14], a period characterized with high market volatility due to the pandemic crisis. In fact, results on the returns exhibit a similar increase during the global financial crisis period, in 2007 and 2008. Therefore, returns demonstrate to be higher during periods of higher market volatility. From Table 6, it is also possible to observe that, for every single period, the evolution of returns, over each additional increment of K, is positive. Nevertheless, for any period, this evolution follows a logarithmic shape, hence supporting the precedent reasoning that the robustness of TA's signals diminishes for increments in K.

4.2.2. Efficacy in Index ETFs

Results obtained in TA's evolution on index-ETFs differ substantially from the ones obtained for individual stocks.

		K = 1	K = 2	K = 3	K = 4	K = 5
Period	[2003 - 2005]	50.0%	49.2%	49.4%	48.8%	47.9%
	[2006 - 2008]	49.8%	47.2%	46.4%	45.8%	45.5%
	[2009 - 2011]	53.1%	55.0%	55.2%	54.2%	52.6%
	[2012 - 2014]	51.5%	50.1%	52.0%	52.0%	53.8%
	[2015 - 2017]	56.9%	54.9%	53.2%	51.6%	50.6%
	[2018 - 2020]	53.3%	50.4%	51.8%	53.4%	52.2%
	Average Efficacy	52.4%	51.1%	51.3%	51.0%	50.5%
	CAGR	0.70%	-0.32%	0.31%	0.80%	0.95%

Table 7- Aggregated evolution of indicators' efficacy for index ETFs

[14] Verifiable in Table III from the appendix

As noticeable in Tables 7 and 8, efficacy does not exhibit a consistent pattern of growth over time, for all levels of K, as previously identified for individual stocks.

		K = 1	K = 2	K = 3	K = 4	K = 5
Signal's Performance	Slope	0.003	0.002	0.003	0.003	0.004
	Pearson R	43.7%	27.3%	35.7%	40.9%	49.2%
	t-statistic	1.946	1.134	1.531	1.792	2.259
	P-Value	3.47%	13.67%	7.26%	4.60%	1.91%

Table 8- Time-series statistical analysis on average efficacy obtained in TA, for ETFs

From Table 8, one can realize how heterogeneous the output data is. Considering a 95% confidence interval, the measured significance on the evolution of TA's efficacy only verifies for some levels of K, not being possible to identify a gradual evolution on this metric over time. Furthermore, as a consequence of the widespread results, no significance was found on the relation between TA's efficacy and DATs, over time. Similarly, results on the evolution of the returns produced by the employed TA strategies are not significant, throughout the periods analyzed, nor are significantly related to the measured evolution of DATs.

From the data above, it is possible to conclude that the pattern on the evolution of TA's efficacy is not clear for index-ETFs. As we are dealing with aggregated data, it is possible that a significant and linear evolution on TA's efficacy only verifies for a certain type of index ETFs. Following the idea that profitable opportunities exist more in younger markets, as formerly described and verified by Ready (2002), Qi and Wu (2006), Hsu et al. (2009), Shynkevich (2012) and P. H. Hsu and Kuan (2005), it was considered essential to proceed the study under this rationale, performing thus a distinct evaluation of TA's efficacy according to the market capitalization exposure. As a result, index-ETFs were aggregated into large-capitalization ETFs (DIA, SPY and QQQ) and small-capitalization ETFs (IJR and IWM).

4.2.2.1. Efficacy and Returns in Large-Cap Index ETFs

		K = 1	K = 2	K = 3	K = 4	K = 5
Period	[2003 - 2005]	47.1%	49.1%	49.9%	49.9%	47.9%
	[2006 - 2008]	49.5%	45.9%	44.0%	44.3%	44.9%
	[2009 - 2011]	52.5%	53.2%	55.5%	53.3%	53.3%
	[2012 - 2014]	48.3%	47.6%	47.7%	47.6%	49.9%
	[2015 - 2017]	53.0%	52.9%	50.2%	47.4%	46.7%
	[2018 - 2020]	51.9%	50.8%	51.4%	52.9%	51.9%
	Average Efficacy	50.4%	49.9%	49.8%	49.2%	49.1%
	CAGR	0.88%	-0.20%	0.11%	0.95%	0.92%

Table 9- Aggregated evolution of indicators' efficacy for large-cap index ETFs

When applied to large-cap index ETFs, the evolution of TA's efficacy does not present evidence of a clear pattern over time, particularly for larger levels of K, as we can observe in Table 9. Undoubtedly, efficacy results seem considerably unrelated throughout the periods, thus suggesting that TA did not evolve significantly for this category of index ETFs. This is further validated by the results in Table 10, evidencing that the inconclusive output observable in aggregated ETFs, in Tables 7 and 8, is not a product of significant evidence being verified for large-cap index ETFs.

		K = 1	K = 2	K = 3	K = 4	K = 5
Signal's Performance	Slope	0.003	0.002	0.001	0.001	0.002
	Pearson R	31.5%	21.2%	14.1%	12.0%	16.5%
	t-statistic	1.327	0.867	0.568	0.483	0.669
	P-Value	10.15%	19.93%	28.89%	31.80%	25.64%

Table 10- Time-series statistical analysis on average efficacy in TA, for Large-Cap Index ETFs

Additionally, from Table 11, it is not possible to find a significant relation on the evolution between TA's efficacy and DATs is obtained, given the limited robustness on the development of the former. In fact, the explanatory power of DATs on the variance of TA's efficacy for large-cap index ETFs is non-significant and, similarly, so does the correlation between both parameters.

		K = 1	K = 2	K = 3	K = 4	K = 5
DATs	Pearson R	23.1%	20.5%	20.3%	30.1%	20.4%
	R Squared	5.3%	4.2%	4.1%	9.1%	4.2%
	t-stat	0.855	0.755	0.747	1.138	0.751
	P-Value	20.4%	23.2%	23.4%	13.8%	23.3%

Table 11- Significance test on the relation between DATs and Efficacy in Large-Cap Index ETFs

These findings allow us to infer that the verified weak significance in TA's evolution, for aggregated index ETFs, in Table 8, likely results from the exposure to small-cap index ETFs included in the sample, as anticipated, following the previously mentioned studies performed in this topic.

		K = 1	K = 2	K = 3	K = 4	K = 5
Period	[2003 - 2005]	0.6%	0.9%	1.0%	1.2%	1.4%
	[2006 - 2008]	1.0%	1.5%	1.6%	1.8%	1.8%
	[2009 - 2011]	0.9%	1.4%	1.7%	2.0%	2.1%
	[2012 - 2014]	0.5%	0.7%	1.0%	1.2%	1.3%
	[2015 - 2017]	0.6%	0.8%	1.0%	1.1%	1.1%
	[2018 - 2020]	1.1%	1.4%	1.6%	2.4%	2.5%
	Average Return	0.8%	1.1%	1.3%	1.6%	1.7%

Table 12- Evolution of returns, over time, for efficient signals on Large-Cap Index ETFs

In Table 12, average returns do not exhibit signs of a significant steady progress throughout the periods analyzed[15], leading us to conclude that the verified trend in returns is a product of random fluctuations over time. It is also noticeable that the average return is lower than that of individual stocks, suggesting that index aggregation considerably reduces TA's efficacy levels. This may be explainable by the level of diversification on sector exposure that indexation provides, not allowing to capture sector-specific returns caused by momentum, over time, as suggested by Moskowitz and Grinblatt (1999), Chordia and Shivakumar (2002) and Hou (2007).

[15] This is further verifiable from the time-series analysis performed in Table V from the appendix

4.2.2.2. Efficacy and Returns in Small-Cap Index ETFs

		K = 1	K = 2	K = 3	K = 4	K = 5
Period	[2003 - 2005]	49.0%	45.7%	45.1%	44.9%	44.3%
	[2006 - 2008]	49.9%	48.5%	48.8%	46.7%	45.9%
	[2009 - 2011]	53.2%	55.6%	53.5%	55.0%	53.3%
	[2012 - 2014]	53.4%	52.6%	57.8%	56.1%	57.3%
	[2015 - 2017]	60.4%	55.4%	54.2%	55.2%	52.9%
	[2018 - 2020]	56.2%	50.2%	53.0%	54.2%	52.8%
	Average Efficacy	53.7%	51.3%	52.1%	52.0%	51.1%
	CAGR	1.53%	0.55%	1.22%	1.27%	1.81%

Table 13- Aggregated evolution of indicators' efficacy on small-cap Index ETFs

In Table 13, results exhibit a clearer pattern of continuous growth on the measured efficacy comparatively with large-cap index ETFs, for each and all of the levels of K. Additionally, it is evident that the CAGR obtained in efficacy is also considerably larger, evidencing that TA has evolved at a significantly higher rate for small-cap indexes ETFs. Lastly, average efficacy reveals slightly higher for this class of index ETFs, for any level of K, providing evidence that TA is more effective in correctly predicting price moves. These results are in line with the literature on this subject, as Ready (2002), P. H. Hsu and Kuan (2005), Qi and Wu (2006), Hsu et al. (2009) and Shynkevich (2012), who observed and concluded that returns obtained from TA's signals are significantly higher for less mature markets.

Similarly to both individual stocks and large-cap index ETFs, TA's average efficacy shows evidence of a decline throughout K, revealing that signal's efficacy fades away as time elapses, since the formation of the trading signal. Consistently with previous results, it is possible to infer that the strategist is more likely to capture a price move if he or she acts on the day after the formation of the trading signal.

		K = 1	K = 2	K = 3	K = 4	K = 5
Signal's Performance	Slope	0.006	0.004	0.006	0.007	0.007
	Pearson R	58.5%	36.8%	54.2%	60.9%	60.7%
	t-statistic	2.884	1.582	2.578	3.071	3.052
	P-Value	0.54%	6.66%	1.01%	0.37%	0.38%

Table 14- Time-series statistical analysis on average efficacy in TA, for Small-Cap Index ETFs

Statistical analysis results, provided in Table 14, further confirm that the significance obtained on the evolution of TA's efficacy for small-cap index ETFs is superior, relatively to large-cap index ETFs, using a 95% confidence interval. Despite the positive results, shown in Table 15, no significant relation was verified in the relation between DATs and TA's efficacy.

		K = 1	K = 2	K = 3	K = 4	K = 5
DATs	Pearson R	34.3%	-10.2%	12.9%	24.9%	26.4%
	R Squared	11.8%	1.0%	1.7%	6.2%	7.0%
	t-stat	1.318	-0.369	0.468	0.929	0.985
	P-Value	10.5%	-	32.4%	18.5%	17.1%

Table 15- Null hypothesis significance test on the correlation between DATs and TA's Efficacy

In fact, R-Squared results indicate that the explanatory level of DATs, in TA's efficacy, is weak, for any level of K, implying that the positive significant evolution verified on the measured efficacy over time, for small-cap index ETFs, is not significantly related to the progress of the retail investor. This leads us to recognize the possibility that other non-measured factors have contributed to the steady evolution of TA's efficacy over time, for this asset class. One possible factor driving these results may relate to a higher institutional presence in small-cap index ETFs, which is not measured by the DATs metric, suggesting therefore that institutions may also rely in TA, as previously documented by Group of Thirty (1985), Frankel and Froot (1987), Taylor and Allen (1992) and Menkhoff (2010). Another plausible factor may simply relate to a possible lack of robustness in the extracted sample of DATs in capturing the RI's presence, in the market. As a matter of fact, online brokers such as *Robinhood*, *Fidelity* and *Ally Invest*, in the U.S., or *Degiro*, *Trading 212* and *eToro*, in Europe, which were unable to include in this study, have a significant market share in the online brokerage industry. As a matter of fact, some of these brokers, as *Degiro*, have no transaction costs associated with ETF products, a factor that may allure investors into such asset type. Howsoever, there is no available data to substantiate these two hypotheses and, thus, no conclusions on this topic can be withdrawn.

Return levels for TA's signals on small-cap index ETFs, exhibited in Table 16, do not show signs of a steady evolution throughout time. In a similar way to individual stocks, returns on small-cap indexes exhibit punctual increases during more volatile periods, such as the global financial crisis and the 2020 pandemic-crisis. Moreover, it is possible to observe that average return increases at a lower rate for each incremental unit of K, indicating that the robustness of returns fades, in the same way as it verifies for both individual stocks and for large-cap indexes.

		K = 1	K = 2	K = 3	K = 4	K = 5
Period	[2003 - 2005]	0.73%	1.03%	1.18%	1.47%	1.57%
	[2006 - 2008]	1.32%	1.62%	1.75%	2.10%	2.09%
	[2009 - 2011]	1.30%	1.85%	2.24%	2.54%	2.66%
	[2012 - 2014]	0.64%	0.98%	1.24%	1.51%	1.69%
	[2015 - 2017]	0.67%	0.91%	1.12%	1.19%	1.39%
	[2018 - 2020]	1.81%	2.38%	2.68%	3.05%	3.31%
	Average Return	1.1%	1.5%	1.7%	2.0%	2.1%

Table 16- Evolution of returns, over time, for efficient signals on Small-Cap Index ETFs

Albeit larger for small-cap index ETFs, when compared to large-cap ETFs, average returns are marginally higher for individual stocks, as we can perceive from Tables 6 and 16. This observation supports the previously discussed topic regarding stock index ETFs, which are characterized by a lower exposure to specific sector momentum, supporting thus the fact that returns obtained in TA for individual stocks are larger.

5. Conclusion

In this research, online brokerage data was extracted with the purpose of assessing the evolution of retail investors' activity, subsequently comparing this metric with the progress of technical analysis' efficacy, over time. We found a positive evolution on both the number of active trading accounts and of daily average transactions, with the latter being significantly correlated with the development of technical analysis' efficacy, for individual stocks. For index-ETFs, evidence supports that trading signals have significantly became more effective in correctly predicting price moves only for small-cap ETFs. Nevertheless, no significant correlation was found between the evolution of this metric and the progress of retail investing. As a result, the main drivers behind the increasing efficacy in technical analysis for small-cap ETFs remain unknown, opening domain for future research on which alternative factors can weigh on the equation. Could institutional investors be driving this evolution in efficacy for small-cap index ETFs?

No significant evolution was found on the returns obtained from technical analysis, for any asset. Nevertheless, according to previous research, we found that technical signals provide higher returns for less mature markets. Additionally, we observed that signals lose some efficacy during the days after their formation and that the rate of this decline has not significantly changed, over time. This fact may suggest that technical analysis better suits short-term strategies which, when combined with fundamentally driven decisions, allow to place orders with a higher precision, optimizing the expected return on a given trade. Alternatively, it may be used in short-term trading.

Regardless, although the drivers behind retail investing are unknown, it is possible to infer that retail investors' behavior may impact the way technical analysis is perceived, at least for individual stocks, for which evidence supports the core motivation of this study that the popularity of technical analysis has been evolving, within the retail investing community, which may be attributable to the surge of both automated technical trading platforms and zero-commission online brokers.

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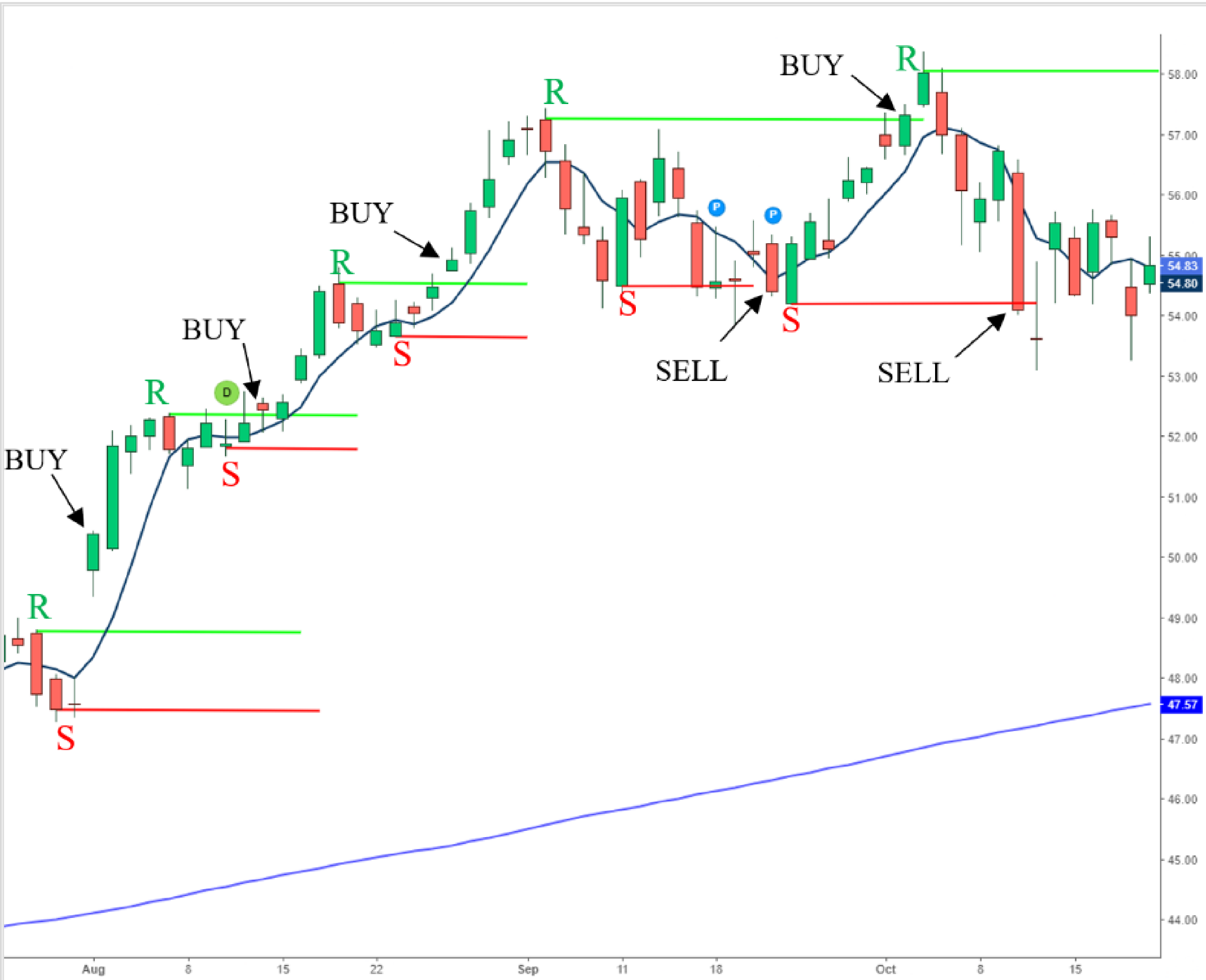
7. Appendix

7.1. Note on Support and Resistance Strategy

Figure 1- Supports and resistances applied to a daily chart on AAPL (26/07/2018 – 19/10/2018)



7.2. Tables

Table I - *Online Brokerage Data*

Year	Total Accounts (Thousands)	Total Equity ($B)	DATS (Thousands)
2006	6,801.1	$1,439.1	238.6
2007	14,205.1	$1,948.5	294.5
2008	15,065.4	$1,541.1	356.5
2009	15,886.4	$1,897.6	383.0
2010	16,468.3	$2,136.5	367.7
2011	17,328.2	$2,262.2	398.6
2012	17,865.4	$2,667.5	370.3
2013	18,539.7	$3,122.9	411.2
2014	19,333.9	$3,476.5	455.8
2015	20,166.0	$3,549.7	494.3
2016	21,292.9	$3,970.6	511.1
2017	27,942.8	$5,015.0	517.3
2018	30,957.1	$5,118.5	668.2
2019	32,580.3	$6,117.0	658.6
2020	31,098.8	$7,017.4	870.8

Table II – *Technical Analysis Efficacy for Individual Stocks*

		K = 1	K = 2	K = 3	K = 4	K = 5	Growth (K=5 / K=1)
YEAR	2003	52.5%	47.7%	46.6%	47.9%	45.5%	-0.13
	2004	48.7%	48.1%	47.3%	48.2%	45.9%	-0.06
	2005	46.7%	45.1%	48.1%	49.3%	49.0%	0.05
	2006	51.9%	48.6%	50.7%	52.8%	49.5%	-0.05
	2007	48.1%	45.4%	43.5%	45.7%	44.7%	-0.07
	2008	51.4%	45.6%	46.1%	46.3%	47.0%	-0.09
	2009	49.3%	55.2%	50.3%	46.8%	50.3%	0.02
	2010	48.7%	50.0%	48.4%	50.6%	51.4%	0.06
	2011	52.3%	49.1%	49.6%	46.6%	49.5%	-0.05
	2012	50.6%	51.5%	49.4%	49.2%	50.6%	0.00
	2013	53.5%	51.2%	50.6%	52.0%	52.3%	-0.02
	2014	49.8%	55.3%	53.9%	49.2%	50.7%	0.02
	2015	51.7%	54.1%	51.9%	49.8%	50.8%	-0.02
	2016	50.8%	49.4%	50.6%	50.0%	53.9%	0.06
	2017	53.2%	56.6%	55.1%	57.3%	59.5%	0.12
	2018	54.2%	56.4%	56.1%	54.3%	55.7%	0.03
	2019	58.3%	56.2%	60.3%	56.1%	58.0%	-0.01
	2020	58.9%	52.8%	50.5%	50.2%	48.0%	-0.18

Table III – *Technical Analysis Returns for Individual Stocks*

YEAR	K = 1	K = 2	K = 3	K = 4	K = 5	Growth (K=5 / K=1)
2003	1.1%	1.8%	2.2%	2.5%	2.9%	1.64
2004	1.1%	1.7%	2.4%	2.5%	2.6%	1.28
2005	1.0%	1.3%	1.9%	2.0%	2.2%	1.27
2006	1.1%	1.7%	2.0%	2.3%	2.7%	1.38
2007	1.1%	1.4%	2.0%	2.5%	2.7%	1.36
2008	2.1%	3.0%	3.7%	3.9%	4.3%	1.08
2009	1.7%	2.3%	2.6%	2.9%	3.3%	0.92
2010	1.1%	1.5%	2.1%	2.2%	2.4%	1.14
2011	1.1%	1.6%	2.0%	2.4%	2.7%	1.52
2012	0.9%	1.4%	1.9%	2.2%	2.3%	1.46
2013	1.0%	1.5%	1.8%	2.0%	2.6%	1.51
2014	0.9%	1.1%	1.6%	1.7%	1.9%	0.98
2015	1.1%	1.4%	1.6%	1.9%	2.3%	1.11
2016	1.0%	1.5%	1.9%	2.1%	2.2%	1.23
2017	0.7%	1.0%	1.4%	1.5%	1.6%	1.31
2018	1.4%	1.9%	2.4%	2.6%	2.8%	0.93
2019	1.2%	1.8%	1.9%	2.2%	2.5%	1.03
2020	2.3%	2.5%	3.7%	4.5%	4.4%	0.96

Table IV – *Technical Analysis Efficacy for Large-Cap Index ETFs*

		K = 1	K = 2	K = 3	K = 4	K = 5	Growth (K=5 / K=1)
YEAR	2003	45.2%	50.8%	48.1%	43.3%	42.6%	-0.06
	2004	47.3%	47.4%	49.5%	54.1%	51.9%	0.10
	2005	48.9%	49.2%	52.1%	52.3%	49.2%	0.01
	2006	44.2%	47.2%	44.2%	43.5%	42.7%	-0.03
	2007	49.4%	42.0%	39.1%	41.1%	42.2%	-0.15
	2008	54.8%	48.6%	48.9%	48.5%	49.9%	-0.09
	2009	55.7%	61.9%	62.5%	63.1%	60.1%	0.08
	2010	55.3%	50.5%	51.9%	51.1%	54.9%	-0.01
	2011	46.5%	47.1%	52.0%	45.9%	45.0%	-0.03
	2012	45.0%	47.4%	49.8%	47.0%	44.9%	0.00
	2013	52.5%	50.9%	51.2%	52.5%	57.0%	0.09
	2014	47.4%	44.4%	42.3%	43.4%	47.9%	0.01
	2015	53.0%	54.0%	49.2%	51.6%	54.1%	0.02
	2016	60.5%	54.8%	55.5%	50.0%	45.7%	-0.24
	2017	45.6%	49.9%	45.8%	40.4%	40.2%	-0.12
	2018	55.2%	51.4%	51.0%	54.0%	51.7%	-0.06
	2019	47.5%	52.1%	54.1%	53.3%	53.7%	0.13
	2020	52.9%	49.0%	49.1%	51.4%	50.3%	-0.05

Table V – *Technical Analysis Returns for Large-Cap Index ETFs*

		K = 1	K = 2	K = 3	K = 4	K = 5	Growth (K=5 / K=1)
YEAR	2003	0.7%	1.0%	1.2%	1.3%	1.5%	1.23
	2004	0.5%	0.9%	1.0%	1.2%	1.4%	1.81
	2005	0.5%	0.6%	0.9%	1.1%	1.3%	1.44
	2006	0.4%	0.7%	0.8%	1.0%	1.0%	1.43
	2007	0.8%	1.1%	1.3%	1.4%	1.3%	0.76
	2008	1.7%	2.6%	2.6%	2.9%	2.9%	0.71
	2009	1.0%	1.5%	1.9%	2.2%	2.5%	1.51
	2010	0.9%	1.3%	1.5%	1.9%	1.8%	1.06
	2011	0.8%	1.3%	1.6%	2.0%	2.1%	1.75
	2012	0.6%	0.8%	1.1%	1.2%	1.4%	1.52
	2013	0.5%	0.6%	0.9%	1.1%	1.2%	1.47
	2014	0.5%	0.7%	1.1%	1.3%	1.4%	1.59
	2015	0.6%	1.1%	1.3%	1.4%	1.4%	1.11
	2016	0.7%	0.9%	1.0%	1.2%	1.3%	0.95
	2017	0.4%	0.5%	0.7%	0.6%	0.7%	0.78
	2018	1.0%	1.6%	1.9%	2.1%	2.0%	0.98
	2019	0.8%	1.0%	1.2%	1.2%	1.4%	0.78
	2020	1.4%	1.7%	1.8%	3.9%	3.9%	1.79

Table VI – *Technical Analysis Efficacy for Small-Cap Index ETFs*

		K = 1	K = 2	K = 3	K = 4	K = 5	Growth (K=5 / K=1)
YEAR	2003	41.8%	43.6%	43.9%	42.5%	40.4%	-0.03
	2004	49.6%	46.9%	41.0%	45.2%	44.5%	-0.10
	2005	55.6%	46.7%	50.3%	46.9%	48.1%	-0.13
	2006	46.5%	49.1%	51.7%	45.7%	46.8%	0.01
	2007	54.0%	46.2%	42.3%	44.8%	43.7%	-0.19
	2008	49.2%	50.1%	52.5%	49.5%	47.2%	-0.04
	2009	48.7%	54.4%	51.4%	56.8%	51.6%	0.06
	2010	57.2%	55.5%	58.5%	56.2%	53.6%	-0.06
	2011	53.8%	57.0%	50.6%	51.9%	54.8%	0.02
	2012	57.9%	55.0%	61.0%	59.5%	60.4%	0.04
	2013	57.4%	60.7%	60.4%	61.7%	59.9%	0.04
	2014	44.9%	42.1%	52.1%	47.0%	51.6%	0.15
	2015	56.0%	55.7%	49.1%	49.1%	45.4%	-0.19
	2016	65.9%	54.9%	55.1%	57.1%	57.4%	-0.13
	2017	59.3%	55.7%	58.5%	59.3%	55.9%	-0.06
	2018	58.5%	47.5%	53.3%	57.4%	53.3%	-0.09
	2019	55.2%	54.9%	51.2%	51.9%	49.2%	-0.11
	2020	54.9%	48.2%	54.6%	53.3%	55.8%	0.02

Table VII – *Technical Analysis Returns for Small-Cap Index ETFs*

		K = 1	K = 2	K = 3	K = 4	K = 5	Growth (K=5 / K=1)
YEAR	2003	0.71%	1.17%	1.28%	1.65%	1.77%	1.48
	2004	0.74%	1.05%	1.11%	1.47%	1.59%	1.17
	2005	0.74%	0.86%	1.16%	1.28%	1.34%	0.82
	2006	0.81%	1.33%	1.43%	1.62%	1.89%	1.33
	2007	1.01%	1.30%	1.47%	1.83%	1.75%	0.73
	2008	2.13%	2.23%	2.34%	2.85%	2.61%	0.23
	2009	1.65%	2.00%	2.30%	2.73%	2.62%	0.59
	2010	1.15%	1.80%	2.21%	2.58%	2.90%	1.53
	2011	1.09%	1.76%	2.23%	2.31%	2.47%	1.26
	2012	0.65%	1.08%	1.37%	1.78%	1.85%	1.84
	2013	0.73%	1.05%	1.22%	1.33%	1.65%	1.26
	2014	0.54%	0.79%	1.12%	1.43%	1.57%	1.90
	2015	0.66%	0.91%	1.27%	1.28%	1.38%	1.10
	2016	0.79%	1.05%	1.21%	1.29%	1.59%	1.03
	2017	0.58%	0.77%	0.88%	0.99%	1.19%	1.05
	2018	0.87%	1.27%	1.38%	1.63%	1.91%	1.20
	2019	0.86%	1.13%	1.31%	1.68%	1.74%	1.02
	2020	3.69%	4.74%	5.35%	5.83%	6.30%	0.71