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Assessment of a Counterintuitive Trading Strategy Based on Market Microstructure

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ABSTRACT

In general, day trading has little support from empirical research and a justified reputation of being dangerously unsound. It often relies on positive price momentum, regardless of the underlying value of the stock. Here, we assess multiple versions of a protocolized day trading strategy that relies on overreaction to bad corporate news, as reflected in premarket prices. Relevant stocks are purchased at the open, when there is an imbalance between buy and sell orders, and held for no longer than a single trading day. The companies in question constitute a basket of deplorables, and the trading strategies rely on mean regression rather than momentum, and also benefit from high levels of inter-day price volatility as the process of price discovery proceeds. Observed returns were positive for all versions of the strategy. Conceptual support is provided by the notion that active money managers have individual incentives to immediately rush toward the door, and those incentives should continue into the future. In conclusion, we have described an unusual and counterintuitive strategy that relies on a conceptually plausible, yet rare and fleeting market inefficiency. It is based on the microstructure of the stock market.

Keywords: behavioral finance, day trading, investor incentives, stock market research.

INTRODUCTION

Colloquially speaking, the efficient market hypothesis (EMH) asserts that stock prices are always correct, and so the only way to obtain above-average returns is to accept above-average risk, manifested by above-average volatility [1]. Among many others, the EMR provides a conceptual basis for the relationship between risk and return.

The EMH was originally derived using the intellectual scaffolding of classical economic theory [2]. For example, if investors are perfectly knowledgeable and rational, if trading is without friction due to trading costs and bid-asked spreads, etc., then any temporary inconsistency between a stock price and its underlying economic value should be quickly removed by arbitrage, broadly defined. For example, if a stock is temporarily a bargain relative to its economic value investors will buy it, causing the price to rise and the bargain to disappear. The underlying mathematics work most simply if the distribution of stock prices is assumed to be a function that is continuous and smooth.

Although it is impossible to prove a negative, indirect empirical support for the EMH has been provided by researchers proposing strategies that hope to beat the market, testing them on historical databases, and discovering that the resulting risk-adjusted returns are unexceptional.

The tests are accomplished by applying an explicit stock selection criterion on January 1 of year 1 in a historical database, selling the resulting portfolio on December 31, calculating the returns, repeating the process on year 2, etc. This distribution of annual returns is used to estimate the mean and the standard deviation, and what is desired is a mean value that is high relative to that standard deviation [3].

Behavioral finance (BF) questions the assumption that investors are entirely rational, and instead postulates that they, like all humans, have an evolution-based tendency toward biases in decision making [4]. For example, one of its creation stories holds that human investors overreact to bad news because their ancestors who assumed that the rustling in the grass was always a tiger ran away, didn't become a meal, and survived long enough to reproduce. BF asserts that biases in decision making can lead to stock prices which are inconsistent with economic value, and thus suggest investment strategies that can be tested as above. The results of this research provide encouragement to both camps: proponents of BF can point to some moderately positive results, whereas proponents of the EMH note that the magnitude of excess returns is neither consistent nor dramatic, and might disappear, at least in part, once sufficiently sophisticated risk adjustment is applied [e.g., 5-19].

There are strong and weak versions of the efficient market hypothesis: an especially compelling one was formulated by Malkiel [2]. It acknowledges (among others) that BF might have a point: for example, market participants can be irrational at times; stocks can be temporarily mispriced, both individually and in aggregate, most dramatically in booms and busts; and stock prices can exhibit greater volatility than suggested by economic considerations such as earnings and dividends. All of this can be directly observed. Nevertheless, Malkiel argues that these "features" don't really matter unless investors can earn above-average returns without accepting above-average risks and, moreover, definitive demonstrations of large "exploitable" anomalies have been lacking. This highlights the importance of research on "market-beating" investment strategies by embedding the results of such research into the statement of the EMH. There is even a "plan B": it is asserted that once such an anomaly is identified, economic incentives will cause market participants to act in a way that removes it going forward (i.e., via arbitrage).

One risk in testing "market-beating" strategies is that the wrong strategies might be used. In particular, if these strategies don't represent what actual investors do (e.g., because they are oversimplifications), and moreover if the direction of this difference is toward poorer observed returns, then the result will be a bias in favor of the EMH. To illustrate: BF-based arguments have been proposed to explain the relative unpopularity of "value stocks" -- essentially, that humans like bright shiny objects and so investors typically prefer companies in exciting new industries to those that make bagels and toilet paper. Value stocks often pay high dividends -- in part because their dependable cash flows and lack of growth imply that excess cash should be returned to shareholders, and part because their stock price is low relative to those dividends. Accordingly, one possible algorithm for a value strategy would be to buy all the stocks in a historical database with annual dividends exceeding a certain level (e.g., 5%). However, a naïve application of this algorithm fails to consider that actual investors would first review the stocks that meet this criterion and eliminate those whose dividend is in danger or are otherwise poor candidates for purchase. Moreover, although some of this review would use

quantitative criteria such as the dividend coverage ratio, in actual practice it would be based on multiple factors, some of which could not be easily operationalized as a formal stock selection algorithm applied to a historical database.

Here, we test an unusual variation of a BF-based investment strategy, and moreover argue that that the resulting market inefficiency is likely to continue into the future.

METHODS

Context: Day Trading

The strategy to be tested involves protocolized day trading. On first blush, day trading provides an especially unpromising context, as its average returns are often negative [20-22]. For example, using extensive trading data from the Taiwan Stock Exchange, Barber *et al* found that fewer than 10% of day traders are consistently profitable: indeed, so much so as to question why the industry persists [20]. Mahani and Bernhardt, though, argued that some day trading has a conceptual justification: namely, that "liquidity traders" (i.e., those with strong incentives to buy or sell a particular stock) are insensitive to price and market makers are often willing to forgo the associated profits associated with exploiting their behavior, thus providing an opportunity for especially skilled day traders to do so [22].

Another conceptual justification for day trading is the persistence of short-term price momentum, regardless of its direction [23]. Indeed, most day trading strategies attempt to exploit such momentum.

Testing Strategies Based on Response to Bad Corporate News

When bad news about a company appears, it is economically reasonable for its stock to drop in price. Depending on the severity of the news as well as its impact on the company's long-term economic prospects, this drop could be small or large, and transitory or longer-lived. While the strongest form of the EMH effectively asserts that the new lower price ought to immediately reflect all the impacts of this bad news, BF holds that this initial response will likely be an over-reaction. Moreover, this over-reaction will lead to negative momentum in the short term, creating a bargain, which will eventually be eliminated by arbitrage, resulting in regression toward the mean (and, thus, superior risk-adjusted returns) in the longer term [18]. The time periods in question depend on context.

Operationalizing the Construct of Bad Corporate News

Some stocks are more volatile than others: for example, a 10% daily drop might be unexceptional for a "high-beta" stock yet rare and informative for a stock that is less volatile. Moreover, a 10% drop in a stock that has recently risen by 50% might simply represent a "correction" carrying relatively little information. We operationalized the construct of "significant" bad news using two criteria. First, using a database of American equities [24], the final premarket price should represent at least a 10% drop from the previous closing price, thus suggesting that the drop has a "cause" that became apparent between the previous close and the start of the next trading day. Second, the final premarket price should be below all prices during the previous month. This second criterion doesn't necessarily imply that the final premarket price is a bargain relative to the stock's economic value -- that is, the construct of

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ultimate interest to the investor -- but does at least imply that the price drop is notable when compared with recent history.

Additional Stock Selection Criteria

In addition, we required that (1) the average trading volume was at least 100,000 shares; and (2) the previous closing price exceed $2 per share. These conditions are intended to reduce friction costs -- for example, by reducing the bid-asked spread and making it likely that the investor can actually receive the prices in the historical database.

Investment Strategy: Conceptual Model

Sufficiently bad corporate news is often delivered outside normal trading hours -- for example, in a press release circulated between the close of a trading day and the open of the next trading day. We postulate that investors initially overreact to this bad news. Moreover, this overreaction takes the form of an unusually high volume of sell orders at the open of the next trading day.

We further postulate that the impetus for the high volume of sell orders at the open is active money managers who have a strong incentive to sell and are less price-sensitive than buyers. Moreover, we postulate that this lack of price sensitivity pertains to their own incentives, especially as they relate to the nature of the bad corporate news. For example, if the sellers are growth investors and the bad news pertains to lower than expected sales growth then the stock no longer fits their stated stock selection criteria. For another example, if the sellers are high dividend investors and the bad news pertains to a reduction in the dividend then the same can be said. This holds true even if the dividend reduction represents sound capital management on the part of the company in question.

We postulate that the reason that buyers are relatively less price-sensitive than sellers is that they anticipate the above price action, based on previous experience. Moreover, there is no requirement that they purchase the stock, and so will only do so at what they believe to be a significant discount. This is economically rational.

Stipulating the above, the question still remains as to why the sellers in question are so highly motivated, and why they choose to immediately sell with relatively little regard to price. Of course, not all potential sellers do so. For those sellers who are motivated to immediately sell, one possible explanation is that they have experienced disasters in other stocks that began with a similar price drop, and the ability to visualize this disaster causes an overestimation of its probability. This is consistent with the tenets of BF, as is the tendency for money managers to herd, and also for losses to have greater emotional impact than equivalent gains.

Another possible explanation is that the portfolios of money managers are reported quarterly, and they don't want to have to explain to their clients why they hold a losing stock. Yet another possible explanation is that their holdings are leveraged, and they must immediately sell in order to meet their margin requirements. These and similar reasons are plausible but not "economically rational" in the sense of only considering the underlying value of the stock in question. In essence, these money managers become liquidity traders. Moreover, unless the

incentives of money managers change, the above tendencies ought to continue going forward [16,18].

Finally, we postulate that opportunity posed by the initial imbalance of sell orders is a fleeting one. Other money managers observe (and, indeed, anticipate) the bargain and act accordingly. After this, the usual rules of price discovery take effect -- potential sellers also wish to sell the stock, although at a favorable price, potential buyers are willing to purchase the stock, but only at a favorable price, etc. With large numbers of shares sloshing back and forth, the price discovery process can be chaotic, and will result in a wide range of prices during the training day. Once prices do stabilize, there is no guarantee of which direction they will ultimately take.

Investment Strategy: Trading Plan

For each stock, we assume that the investor uses a "buy on the open" order, and so makes the first trade of the day. The price should be similar to the last premarket price. Once the stock is purchased, the investor is assumed to immediately submit a limit order to sell the stock for profits of 3%, 5%, 7% or 10%. For example, if a stock is purchased at the open for $10.00, the sell orders would be at $10.30, $10.50, $10.70 and $11.00. If the limit orders aren't triggered, the investor sells the stock on the close. We also consider a strategy where the investor always sells the stock on the close (i.e., without using a limit sell order during the day).

For example, if the above stock reaches a high price of $10.40 and closes at $9.80, the limit order would be triggered at 3% but not at 5, 7 or 10%. For the 3% limit order, the investor gains $0.40 (i.e., $10.40-$10.00), and for the other limit orders they lose $0.20 (i.e., $9.80-$10.00). Trading costs are assumed to be trivial.

Investment Strategy: Assessment

Using consecutive trading days beginning with 16 May 2024, the selection criteria were applied until 30 examples were accumulated. For each stock identified by the selection criteria, using a historical database [25] we report the following prices for the trading day in question: open, low, high, and close. This information is used to generate the daily returns for each of the above five strategies. Daily returns were summarized by means, standard deviations, quantiles, geometric means, and 1-sample t-tests.

For strategies that sell when a threshold value is reached, we also report the number of stocks for which the threshold was met.

RESULTS

Table 1 summarizes the opening, low, high and closing prices for our sample of 30 stocks. Table 2 summarizes the returns. Figure 1 provides a visual depiction.

Table 1: Prices on the day of a large drop

Symbol	Open	Low	High	Close
SPIR	8.50	8.27	10.29	9.91
UA	6.23	6.11	6.86	6.64
DXC	15.87	15.70	16.90	16.52
CBRL	50.14	48.18	51.74	48.98

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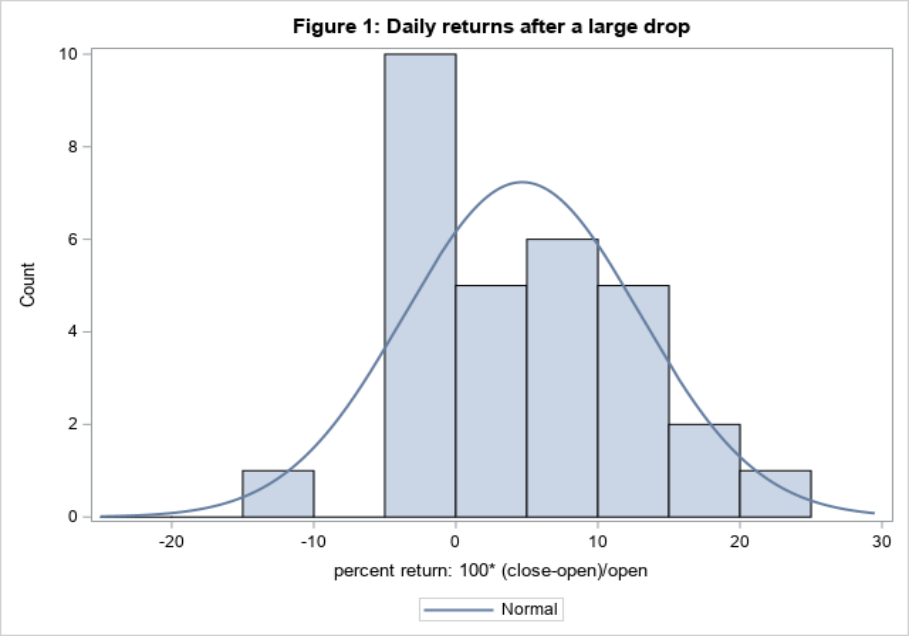
PLAB	23.63	23.55	26.67	26.32
EDBL	1.87	1.82	2.39	2.30
VSAT	15.81	15.60	16.80	15.74
GCT	26.32	25.22	29.95	29.83
CYTK	49.25	47.59	50.24	48.98
VFC	11.48	11.00	12.19	11.97
VSTM	4.69	4.00	5.25	4.12
SMMT	3.51	3.20	3.95	3.38
WDAY	232.19	219.39	236.95	220.91
CRM	223.40	212.00	225.09	218.01
MAXN	1.71	1.45	2.29	2.02
PATH	12.60	11.71	12.70	12.07
KSS	20.69	19.58	21.29	21.02
BRKR	65.50	64.75	68.00	65.68
S	14.77	14.33	17.18	16.83
CRBU	1.92	1.75	2.30	2.14
DBI	8.70	8.55	9.50	8.80
AX	44.10	44.10	50.00	48.95
PHUN	5.54	5.51	5.87	5.86
GCTS	4.11	3.85	4.11	3.98
MED	20.43	19.90	22.13	22.02
MNMD	7.47	6.59	7.58	7.42
BIG	3.03	2.72	3.22	2.88
CXM	8.41	8.33	9.39	9.20
FIVE	107.95	106.21	119.51	118.72
BMEA	3.88	3.61	4.35	4.14

Table 2: Daily returns after a large drop

Strategy	Mean	Standard deviation	Geometric mean	25th quantile	50th quantile	75th quantile
Range (%)	16%	11%	8%	8%	12%	20%
No cap	1.047	0.083	1.044	0.977	1.042	1.114
3% cap	1.018	0.024	1.018	1.030	1.030	1.030
5% cap	1.029	0.034	1.029	1.001	1.004	1.005
7% cap	1.035	0.045	1.034	0.994	1.070	1.070
10% cap	1.047	0.057	1.044	0.994	1.068	1.110

The first row of Table 2 highlights the amount of inter-day variation in stock prices. The mean range (i.e., (high-low) / low)) is approximately 16%. Visually, the bars on a stock chart would be exceptionally tall (and the trading volume would spike). This provides encouragement to strategies that take advantage of temporary spikes in prices during this particular trading day. The second row of Table 2 reports within-day changes in price (i.e., (close-open)/open). Of note, the mean change in price exceeds 4% ($p<0.01$). The medians and geometric means are similar.



The remaining rows of Table 2 illustrate the impact of capping profits. For example, when capping profits at 10%, the trade-off is that profits are reduced for the 8 stocks that have a daily return exceeding 10%, but are increased for the 6 stocks that reached the 10% threshold but closed with a daily gain of less than 10%. This trade-off had little impact on the mean return, but did reduce the variability in returns (and, thus, increased risk-adjusted returns). The number of stocks (out of 30) that reached their target price was 23, 21, 16 and 14 for 3%, 5%, 7% and 10% targets, respectively. All mean returns were significantly different from 0 ($p<0.01$).

In general, capping the potential profits reduced both the mean and standard deviation of the daily returns, which is consistent with expectations. The largest ratio of the mean to the standard deviation was for a 5% profit cap, closely followed by a 10% cap.

Interpretation

Our scientific premise considered two possibilities. The "strong" hypothesis is that the initial imbalance at the open will produce a temporary bargain. In that case, the trading strategy that holds stocks until the end of the trading day should have a positive expected return. The "weak" hypothesis is that the initial imbalance will result in a correct opening price, and also that unusually volatile trading should take place on that day. In that case, the trading strategies with limit orders might have a positive expected return, simply as a way of harvesting the resulting noise. Indeed, both hypotheses can simultaneously be true, in which case all of the strategies being tested should perform well. We observed that all strategies generate a positive return, supporting both hypotheses.

DISCUSSION

A vast literature assesses the performance of BF-based investment strategies designed to "beat the market" (e.g., [5-19]). Positive results undermine the EMH, whereas negative results provide the EMH with indirect support. Here, we assessed multiple versions of a strategy that

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is based on the predictable behavior of those money managers who respond to bad news by rushing to sell on the open. We postulated that (1) the imbalance between buy and sell orders at the open causes the opening price to overestimate the economic impact of the bad news; and (2) the trading day will have a high level of price volatility. Both of these postulates were supported by the data.

A trading strategy that is directly based on the first postulate is to enter a buy on the open order at the start of the trading day and a sell on the close order at the end of that day. Its daily return was 4.7%, with a standard deviation of 8.3%. A trading strategy that is directly based on the second postulate is to enter a buy on the open order and then immediately enter a limit sell order with a specified percentage profit. If this order goes unfilled during the trading day, the stock is sold at the close. The highest risk-adjusted return set the profit threshold at 5%, and had a daily return of 2.9% with a standard deviation of 3.4%. Setting the profit threshold at 10% generated a daily return of 4.7% with a standard deviation of 5.7%. The mean return was similar to always selling on the close, but with less volatility.

The capped strategies have a maximum possible gain and an unlimited possible loss, and so are "short volatility". The main risk is that the stock price will fail to meet the price target at any point during the trading day and then close at a loss. The main protection against large losses is that the bad news is already out, and a large price drop will have already happened at the time the stock is purchased. With stocks being held for a single day at most, additional bad news is relatively unlikely, and the primary risk is that, as the process of price discovery proceeds throughout the trading day, the market's conclusion will be even more pessimistic than what is reflected by the opening price. No "black swan" events where profound price drops after the open were observed, although they are possible and are a generic concern for strategies that are short volatility. In our empirical assessment gains accrued at a more rapid pace than losses.

Slippage due to trading costs isn't considered, nor is the impact of taxes. The hope is that returns are sufficiently high that they will overwhelm the above sources of slippage. It should be emphasized that the returns reported here are daily, not annualized.

That money managers tend, in response to bad news, to sell at (or near) the open is an empirical observation, based on the price drop and relatively large volume of trades that is typically seen -- what is being postulated is not that this behavior takes place but, instead, is its underlying causes. Our conceptual model includes general cognitive biases (e.g., overreaction, herding) described by BF as well as characteristics that are specific to those money managers (e.g., use of leverage implies the need to immediately liquidate losing holdings before the losses increase, urgency to sell when a stock no longer meets their selection criteria). So long as these characteristics of active money managers remain in place this opportunity should continue going forward [16,18].

The maximum holding time for all the strategies we assessed was a single day. Thus, they are essentially protocolized day trading strategies. Indeed, when compared with a typical day trading strategy they are rather counterintuitive. First, some of the initial price drops exceeded 50%, and corresponded to news that was truly bad -- for example, earnings requiring restatement, regulators halting clinical trials, etc. A portfolio of such stocks is a basket of

deplorables, and certainly not a collection of companies in which to take pride. However, it might be argued that this is precisely the sort of deep value portfolio that a BF perspective would believe to be potentially undervalued.

Second, day trading strategies are often based on one of two premises: (1) non-directional day trading strategies rely upon noise harvesting; and (2) directional day trading strategies rely upon price momentum. Here, however, our "buy-hold" strategy relies upon mean regression (i.e., the opposite of momentum), whereas the "capped" strategies rely on noise harvesting, with additional support provided by the mean-regression-based possibility that the opening price represents an overreaction that, in general, ought to be corrected during the course of the trading day. This is consistent with the notion of identifying and taking advantage of liquidity traders, which Mahani and Bernhardt found promising [22].

An especial challenge for assessing investment strategies using historical databases occurs in the step where the statement of the putative market inefficiency to be exploited is translated into a stock selection criterion, and this study is no exception. Our selection criteria (i.e., expected price drop of at least 10%, leading to the lowest price within the 30-day period) is a decidedly imperfect surrogate for the underlying construct, which is a trading day (1) with a large amount of price volatility; (2) that starts with a large price drop; (3) which is caused by money managers with a strong incentive to sell; and (4) begins with an economically acceptable price. In practice, and recognizing that being the lowest price within the most recent 30 days doesn't necessarily imply that it is economically justified, the investor would apply additional stock selection criteria to try to weed out overvalued stocks and also news that calls the economic viability of the company into question: to the extent that they can successfully do so our results might underestimate expected returns.

Variations of this trading strategy are possible. For example, an additional margin of safety could be obtained by replacing a "buy on the open" with a "limit buy" order having a purchase price somewhat below the last premarket trade, at the risk of this order going unfilled. Similarly, a "sell on the close" order could be replaced with a "limit sell" order.

This particular strategy is only recently feasible. For example, it relies on real-time databases of premarket trades to identify candidate stocks, the ability to find corporate press releases online, and the use of online brokers to submit orders in real time while charging minimal fees. Once stock selection criteria are reviewed, the implementation of this strategy can be accomplished with a minimal commitment of time. After the buy at the open order is filled, the limit sell order can be immediately placed. In the absence of a confirmation that the stock has been sold, the investor would login late in the day and either enter a sell on the close order or execute the sale before the close.

Elsewhere, we have described other investment strategies that attempt to take advantage of the greater volatility in stock prices than suggested by economic considerations such as earnings and dividends [3,26,27]. One strategy is to write covered call options (i.e., monetizing price volatility directly), another is to select mean-reverting stocks and sell them the first time they generate a small profit (i.e., doing so indirectly). The current strategy is an extreme variation on this theme -- indeed, so extreme that "investment" is replaced by protocolized day

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trading. It also differs from the previously considered strategies by targeting a specific market inefficiency (i.e., the behavior of active money managers in response to bad news) rather than a general one (i.e., the general tendency to overly speculate, causing excess volatility).

These who are philosophically wedded to the notion that stock markets are, as a whole, efficient, would likely be unconcerned by the current counterexample which, even if valid, only affects a tiny number of stocks (on average, 1-2 per day) for a fleeting moment on any particular trading day. We agree, and would classify the putative inefficiency in question as limited to a highly specific aspect of the microstructure of the market. Nevertheless, we believe that it might be useful as a proof of concept, and especially as an illustration of how Malkiel's objection about "plan B" can be addressed [2] -- namely, by not only describing a market inefficiency, but one which is likely to continue even when other market participants become aware of it. Indeed, it can be argued that the daily trading pattern occurring here illustrates that price-sensitive investors have already anticipated that the opening price is likely to reflect an overreaction, and the price volatility observed during the trading day is driven by others attempting to take advantage of this mispricing (counterbalanced by sellers attempting to escape from an unfortunate investment). This adjustment doesn't occur as a smooth continuous function as assumed by classical economic theory, because of the large volume of shares being traded.

A natural follow-up study would ask whether similar results would be observed for any stock that drops by more than 10% premarket -- in other words, by eliminating the requirement that the final premarket price be lower than any price during the preceding month. From the perspective of the EMH this change ought not to make a difference -- the new price ought to be "right, perhaps after a brief correction to undo he impact of the imbalance on the open" -- although this assertion is open to empirical testing.

The main limitations of the study pertain to sample size and generalizability. The sample size of 30 was moderate, albeit sufficient to demonstrate statistical significance. If a database with archived premarket prices could be found the stock selection criteria could be automated and the sample size and temporal coverage increased. Only 1-2 stocks met the selection criteria on a typical day, and so the stocks in question are highly selected. Moreover, it is uncertain whether these results hold during time periods with strongly rising or strongly falling prices. Essentially, there is an implicit assumption that the daily trading patterns in question depend far more on the characteristics of the individual stocks being studied than on the background behavior of the market as a whole.

In general, day trading often belongs in the category of buying and flipping overpriced assets, and has a justified reputation of being economically unsound and potentially catastrophic to execute in practice [20-22]. The strategies considered here are counterintuitive, in that they illustrate a special case where day trading (literally so, with stocks held for no longer than a single trading day) has a positive expected return.

CONCLUSION

In conclusion, we have described an unusual and counterintuitive strategy that relies on a conceptually plausible, yet rare and fleeting market inefficiency. It is based on careful

consideration of the microstructure of stock market trading. To paraphrase Yogi Berra: you can observe a lot just by watching [28].

References

[1]. https://www.investopedia.com/terms/e/efficientmarkethypothesis.asp. Accessed April 14, 2024.

[2]. The Efficient Market Hypothesis and Its Critics, by Burton G. Malkiel, Princeton University, CEPS Working Paper No. 91, April 2003.

[3]. Samsa G. A new critique of the traditional method for empirically estimating the returns associated with strategies of stock investment: impact of fixing the investment horizon. 2024. Bentley University Case Studies in Business Industry and Government Statistics 5(2), 2014;5(2):102-110.

[4]. https://www.investopedia.com/terms/b/behavioralfinance.asp.

[5]. Bergen, J.V. Jason Van (17 February 2004). "Efficient Market Hypothesis: Is the Stock Market Efficient?" (http://www.investopedia.com/articles/basics/04/022004.asp). Investopedia.

[6]. Bogle., J.C. The arithmetic of "all in" investment returns. Financial Analysts Journal, 2014. 70(1): p.1-9.

[7]. Daniel, K., Hirshleifer, D., & Subrahmanyam, A. Investor psychology and security market under-and overreactions. Journal of Finance,1998. 53:p.1839–1885.

[8]. Dreman,D.N., & Berry, M.A. "Overreaction, Underreaction, and the Low-P/E Effect". Financial Analysts Journal. 1995.51(4):21-30.

[9]. Duxbury, D. Behavioral Finance: Insights from experiments I: Theory and financial markets. Review of Behavioral Finance,2015. 7(1):p.78 -96.

[10]. Fama, E., & French, K. "Dissecting Anomalities". Journal of Finance. 2008. 51(1):p.55-84.

[11]. Heukelom, F. Behavioral economics. New York, NY: Cambridge University Press, 2014.

[12]. Kahneman, D., & Riepe, M. W. Aspects of investor psychology. Journal of Portfolio Management, 1998. 24, 52–65.

[13]. Lakonishok, J., Shleifer, A., & Vishny, R. W. Contrarian investment, extrapolation, and risk. Journal of Finance,1994. 49: p.1541–1578.

[14]. Malkiel, B.G. A Random Walk down Wall Street: the Time-Tested Strategy for Successful Investing. New York: W.W. Norton, 2003.

[15]. Sahi, S. K., Arora, A. P., & Dhameja, N. An exploratory inquiry into the psychological biases in financial investment behavior. Journal of Behavioral Finance,2013. 14:p.94–103.

[16]. Samsa G. Now that behavioral finance has demonstrated that investor behavior is (somewhat) predictable does that mean that arbitrage must make the biases in question disappear? Archives of Business Research. 2019:7(8),146-160. DOI:10.14738/abr.78.6902.

[17]. Samsa G. The efficient market hypothesis is usually tested indirectly: what happens if a direct approach is used instead? Archives of Business Research. V9(6), 45-50. June 2021. DOI: https://doi.org/10.14738/abr.96.2021.

[18]. Samsa G. Why does momentum persist? Archives of Business Research, 2020, 8(11), 119-125. https:/doi/org/10.14738/abr.811.2020.

[19]. Shiller, R. J. From efficient markets theory to behavioral finance. The Journal of Economic Perspectives, 2003. 17:p.83–104.

[20]. Barber B, Lee Y-I, Liu Y-J, Odean T. Do day traders rationally learn about their ability? SSRN Electronic Journal. 2014. DOI:/10.2139/ssrn.2535636.

[21]. Garvey R, Murphy A. The profitability of active stock traders. Journal of Applied Finance. 2005, 93-100.

[22]. Mahani R Bernhardt D. Financial speculators' underperformance: learning, self-selecion, and endogenous liquidity. Journal of Finance. 2007:62, 1313-1340.

[23]. https://www.investopedia.com/terms/m/momentum.asp

[24]. https://www.tradingview.com/markets/stocks-usa/market-movers-pre-market-losers/

[25]. https://finance.yahoo.com/quote/.

[26]. Samsa G. A simple method for amateur investors to analyze covered call options. Archives of Business Research. 15 Jan 2020. 8(1):227-235.

[27]. Samsa G. If you plan to write a covered call option which will expire does traditional option pricing theory apply and, if not, what can replace the Greeks? Archives of Business Research, 2020, 8(9), 27-36. https://doi.org/10.14738/abr.89.2020.

[28]. https://www.mlb.com/news/yogisms-best-yogi-berra-sayings