

The Monty Hall Problem and High-Frequency Trading: The Value of Information and Speed Combined Together

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Abstract. *The counter-intuitive probabilistic features hidden within the Monty Hall problem display a strong relationship to the dynamics of stock market. Decisions in either system are driven by information and decision-makers may decide whether sticking to their original choice or switching to an alternative one based on their epistemic state. One aspect of this paper deals with the connections between optimal information management suggested by the Monty Hall problem and its application to financial markets. However, in modern markets, mere possession of information superior to most other participants cannot guarantee abnormal returns if it is not supported by low execution latency. This is the second aspect discussed in the paper. The conclusion of the paper is that information and speed combined together create the conditions needed to achieve above average returns. It comes to no surprise that heavy investments go to increasing trading speed, potentially leading to a technological ‘arms race’ that carries high private benefits and high social costs. The main contribution of this paper is the use of simple mathematics to demonstrate how publicly available information, when used at high speed, may ensure abnormal market returns for the few ultra-fast traders, so disrupting the social purpose of stock markets.*

Keywords: Abnormal return, High-Frequency Trading, Monty Hall Problem, Technical Analysis

JEL Codes: _G11, G12, G15

1. Introduction

1.1. The Monty Hall Problem

The Monty Hall problem (MHP or ‘the Problem’) is a TV game show that surged to the honor of academic debate. The Problem is well known. The game host (a male) shows the player (for example, a lady) three closed doors. Two doors conceal no prize and only one conceals a car. The game starts with the player selecting one of the doors. Then, the host knowingly opens an empty door and offers the player a chance to change her mind. She will get whatever is concealed behind the door selected on her second choice. The question is: should the player stick to, or switch, her initial choice? (The right answer is switching, as it increases winning chances from 1/3 to 2/3). With a couple of letters to The American Statistician in 1975 (Selvin 1975a; Selvin 1975b), the biostatistician Steve Selvin opened a Pandora Box that has not closed yet. Actually, this apparently simple, yet counterintuitive, problem is so rich in details and subtleties to allow Dr. Jason Rosenhouse to write a whole book on many different aspects of statistics, all springing out from the Monty Hall problem (Rosenhouse 2009).

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1.2. Technical Analysis

Technical Analysis (TA) “refers to the study of the action of the market itself as opposed to the study of the goods in which the market deals” (Edwards et al., 2001, p.4). The theory is summarized by Kirkpatrick and Dahlquist (2011):

- (a) stock prices are determined solely by the interaction of demand and supply;
- (b) stock prices tend to move in trends;
- (c) shifts in demand and supply cause reversals in trends;
- (d) shifts in demand and supply can be detected in charts;
- (e) chart patterns tend to repeat themselves.

A trend is a price movement into a definite direction that continues for a sufficiently long period of time to be identified and taken advantage of. Trends can be identified through statistical tools. Lo (2004) proposed the Adaptive Market Hypothesis, a framework according to which agents adjust their strategies as market conditions change, following a standard competition-adaptation-selection-evolution scheme. More recently, Alonso-Monsalve et al. (2020) focused on neural networks but still making use of TA. TA makes large use of patterns. A pattern is a graphical price profile that has a lower and an upper bound. Within such a band, prices can and do move freely but their movements are controlled by band boundaries. If permanence within a band goes on long enough to allow identification and exploitation, profit probabilities increase. The patterns sought by tech-analysts are the most varied and even though recognizing a pattern ex-post is pretty easy, identifying one ex-ante is not. Bulkowski (2021) indicates, for various types of patterns, the breakout failure rate and the average price rise or decline in case of upward and downward breakout, respectively. The break-even failure rate represents the percentage of days in which returns is negative, that is, the trader loses money and the average price rise/decline represents the average daily price change - a rise in the case of a bull market and a decline in the case of a bear market. The author uses several databases to carry out the analysis, the main one consisting of 500 stocks, with all data referring to the period 1991-2004. The conclusion that the author draws is that all chart patterns analyzed in the research show rather low break-even failure rates. That means that identifying the right patterns and closely following them, ensures consistent above average returns with very few nasty surprises over time. Imagination is not amiss among TA researchers. Some proposed a link between price movements and Fibonacci numbers sequence (Krausz n.d.), psychology-based trading, Bollinger Bands and Relative Strength Index (Thorpe 2000a), Stochastic Oscillators (Thorpe 2000b), Candle Sticks (Bigalow 2002; Nison 1991), and lots of charts, momentums and moving averages.

Aside from Technical Analysis, recent papers suggested some kind of deep learning (a branch of Artificial Intelligence) to identify optimal trading strategies (Abergel, 2020; Briola, 2020). Ferreira et al. (2021, p.30898) revised 2300+ papers to identify techniques based on “portfolio optimization, stock market prediction using AI, financial sentiment analysis, and combinations [thereof]”. Petukhina (2021, p.19) suggests that “it is easily possible to derive sentiment and therefore market reactions from Twitter, Facebook, Stocktwits, or similar”. TA is just one example, albeit perhaps the most widely adopted, but by no means the only technique, to make educated market guesses.

1.3. High-Frequency Trading and the Importance of Speed

While a combination of MHP and Technical Analysis may improve the chances of profitability, High-Frequency Trading (HFT) adds speed to the recipe to ensure abnormal returns. Speed has always been an important factor in financial markets. It is not without reason that financial traders have been early users of technological advancements in communication speed (Markham, 2015). Nowadays, communication speed is

achieved through dedicated submarine cables, fiber optics and microwaves. Beunza et al. (2011) enumerate four lawful categories that trading algorithms can be grouped into: market-making, inter-market arbitrage, statistical arbitrage, and order anticipation strategies. All these strategies benefit from information speed. Hasbrouck and Saar (2013), analyzing publicly-available NASDAQ data, suggest that low-latency trading improves market quality measures: decreases bid-ask spread, increases liquidity, and reduces short-term volatility. To achieve low latencies, HF traders make use of recent technologies, whence it comes the parallel with the notorious arms race of the Cold War in the 1970s and 80s. Leber et al. (2011) explain how any mean is allowed to reduce latencies: Field Programmable Gate Arrays (FPGAs hardware, FAST (FIX Adapted for Streaming) communications protocols, co-location (location of computers within the exchange premises), and efficient software. Bare-bone algorithms allow saving precious microseconds sacrificing the depth of financial analysis. Fiber optics telecommunications that used to take 6.6 milliseconds between the New York Stock Exchange in Mahwah, New Jersey, and the Chicago Mercantile Exchange data center in Aurora, Illinois, have been abandoned in favor of microwave towers, in order to shave off 1.6ms along the trip (MacKenzie et al., 2012; Lewis, 2014). The main contribution of this paper is providing a demonstration of how a combination of information and speed may attain above average return for the few to the detriment of the rest of the trading community.

1.4. Why Is the Monty Hall Problem Relevant to the Stock Market?

The scenario depicted by the MHP is akin to what happens in the stock market. In the beginning, a TA trader evaluates the conditions and decides on a certain strategy but does not implement it. Initially there are many possible choices among patterns and, in the stock market similarity, the market itself ‘opens the doors’ by successively excluding inapplicable patterns. Indeed, Siddiqi (2009) finds a relationship between that cognitive bias that he calls ‘the lure of choice’ at the individual level and the intensity with which it impacts market prices. As fractions of a second go by, the trader acquires more information about price trends and updates her strategy accordingly, until when the final decision is made and she submits the order to the market (Herbranson & Wang 2014). A trader stands facing the market as in the Monty Hall example above. She/he gains higher chances to close their deal profitably as patterns selection based on more, and more recent, information guarantees better outcomes. Similarly, to the MHP, pattern-driven information increases the chances to enter profitable trading. Overall, Kirkpatrick and Dahlquist (2011), consistently report pattern profitability above 80% over the observation period. If we assume N trades during a certain time and the minimum goal is avoiding a loss in that period, with combinatorial calculus it is easy to work out the probabilities of achieving the goal. It can be assumed that all trades involve the same amount of money and therefore the goal becomes getting some losses lesser than the number of wins.

2. Method

The method to verify that a combination of TA and ultra-fast trading is capable of achieving above-average performance is twofold. In the first place, it has been devised a sound technique for ensuring a break-even failure rate of slightly less than 50%. In this case, TA seems a reasonable choice although it is by no means the only one. Nevertheless, mere use of TA does not ensure consistent abnormal return because the technique is very well known and thousands of market traders use it every day. Therefore, to defeat the competition, orders must be executed at very high speed, with HFT. Combinatorial calculus is used to show that the combination of TA and HFT (meaning a very large number of trades per day) results in consistently profitable trading, which converts into above-market returns. The application of MHP to the stock market can be depicted as follows. The HFT algorithmic trader observes the stock market, through data quotation. When the situation seems appropriate, a hypothesis is made about a TA pattern. The trader keeps observing

market movements and verifies whether such movements comply with the chosen pattern. If they do not, the trader selects a different pattern that resembles more to the movements of stock prices. This process repeats until the algorithm evaluates that a sufficient level of confidence in the chosen pattern has been reached. If so, the order executes, otherwise it keeps observing the market and postpones its decision. It must be noted that trading can continue around the clock. Because of HFT, deals may occur several thousand times per day.

3. Results

3.1. How the MHP applies to the stock market: Technical Analysis

Table 1 and Table 2 are derived from Bulkowski (2021), who uses 1991-2004 data from a database containing 500 stocks, most from NYSE, AMEX, and NASDAQ. Although his research displays a large number of statistics, graphs and discussions, Tables 1 and 2 just show the two most fundamental numbers: break-even failure rate and average price rise/decline, in the case of bull and bear markets. The results are varied.

3.1.1. Upward Breakouts

In case of upward breakouts (Table 1), the break-even (B-E) failure rate ranges from 0% with 69% and 42% return in bull and bear markets, respectively (pattern Flags High and Tight) to 22% or 20% (pattern Scallops Descending with 22% or 15% return (patterns: Scallop Descending in a bull market and Right-Angled and Ascending in a bear market). Break-even failures are expected to be lower than 8% at a 95% confidence level if averaged across all patterns in either market, whereas average rise or decline, at the same confidence level, stays above 25% and 35% in the bear or bull market, respectively.

<Table 1 about here>

3.1.2. Downward Breakouts

In the case of downward breakouts (table 2) statistical analysis yields rather bold results, too. B-E failures remain pretty low, between 0% and 2% (Pennants in the bear market and Flags in the bull market) with 23% to 44% return (Head-and-Shoulders Tops Complex and Diamond Bottoms, in bull and bear market, respectively).

<Table 2 about here>

The maximum B-E failures reach 27% (Scallops Ascending) in bull market and 20% (Scallops Descending) in bear market. Minimum returns range between 14% (Scallops Ascending) in bull market and 18% in bear market (Broadening Bottom). At 95% confidence, the average break-even failure is below 12% for a bull market and below 7% for a bear market. The average rise/decline is no less than 17% (bull market) and above 23% (bear market), respectively. The previous analysis provides some indication of the overall value of chart patterns and Technical Analysis when they are being correctly applied. Overall, following TA patterns is, according to Bulkowski (2021), a good choice. As highlighted even by the boldest followers of such a technique, the difficulty is to correctly identify the right pattern without being deceived by other similar, but incorrect, patterns. Actually, in markets populated by a crowd of atomized, uninformed, day-traders (as is the case of modern markets), the very large number of probability judgment error (noise) is

balanced out by the huge number of ultra-fast informed trades launched by a tiny number of high-frequency traders.

3.2. How the MHP applies to the stock market: High-Frequency Trading

An original relationship between the MHP and HFT has been revealed by Seyfert (2016) by highlighting how the same data owned by slow and fast traders leads to different conclusions and therefore to different behaviors in the market. Things must not only be done right; they must also be done fast. Success will only reward those who get there first. This consideration naturally leans toward ultra-fast trading. Indeed, HF traders can make use of very frequent information arriving sequentially (given by price movements) to adapt their strategies to the most suitable TA pattern. Staying ahead of the competition in ultra-fast trading is the goal. This competition, according to several authors, such as Aquilina et al. (2022), and Teall (2023), among others, leads to an arms race where, the subject that could not follow continuous increase of costs just to stand still, admits defeat and surrenders. Indeed, HFT profits started and continued high in the early years of the XXI century (Arnoldi, 2016), only to get flat in the second phase of HFT lifetime (Verousis et al. 2018), to rise again recently with the introduction of Artificial Intelligence techniques (Aït-Sahalia & Saglam, 2024).

3.3. Applying combinatorial calculus

Math somehow supports the hopes of technical traders although theory is not always complied with by the practice. Nevertheless, if the percentages even remotely resemble Bulkowski's figures, abnormal returns will be pocketed. The probability of k success in a binomial experiment is

$$P(k) = P(k \text{ successes}) = {}^nC_r p^k q^{(n-k)} \quad (1)$$

where P is the probability of achieving k successes, ${}^nC_r$ is the combination of k elements from a set of n distinct objects, p is the probability of one success and q (=1-p) is the probability of one failure. In order to maximize chances of success, n, a number of daily trades must go up by increasing the frequency of trades, using HFT. When TA goes hand in hand with ultra-fast trading, things, at least in theory, appear very rosy. Figure 1 shows the increase in return safety for break-even failure rates equal to 49%, 48% and 47% (all much higher than in Kirkpatrick & Dahlquist, 2011) as daily trades increase. Even more explicative are tables 3, table 4 and table 5, showing the number of yearly break-even failure rates in correspondence with the number of daily trades, Failure frequency shows the number of 'losing days' per year (assuming 250 trading days).

<Figure 1 about here>

These tables clearly show that in the presence of even modest return safety levels (i.e. break-even failures rates just below 50%), when the number of trades is low, traders enjoy a relatively low number of expected bad days in a year.

<Table 3 about here>

<Table 4 about here>

<Table 5 about here>

This is the typical case of professional traders adopting TA tools. Yet, tables 3, 4 and 5 show combinatorial calculations for up to 10,000 trades per day. That is far from an impossible occurrence for HFT during the 27,000 seconds in a typical trading day, 9:00 am to 4:30 pm. As the number of trades increases, break-even failure rates drop dramatically, reaching, in case of break-even failure rate = 47% and 10,000 operations per day, the rather safe probability of closing with a loss one day every nearly four-and-a-half million years.

4. Discussions

4.1. MHP, TA and HFT: Putting All Together

The Monty Hall Problem provides a framework that some authors find suitable for studying the behavior of market traders, highlighting the importance of information and its correct use. Of course, this is not only applicable to TA and HFT but in the environment created by the combination of both, information assumes a special meaning. Although TA patterns may unwind over weeks or months, they may also appear at very short timeframes and consequently make use of information at the sub-second level. Traders can modify their initial decision according to information arrived over the very last few seconds, if they are humans or microseconds, if they are computer algorithms. If a price movement does not follow the pattern initially assumed, the smart trader will switch rather than stick, picking up the one that most closely adapts to the actual profile that unrolls in the market. As in the MHP, the initial technical analyst choice is very likely to be wrong, and the more likely wrong the higher the number of patterns available. Again, switching is the correct strategy. Technical Analysis theory has produced a reasonably large number of profitable patterns and ensures that, if the correct pattern is identified and carefully followed, then fruitful gains will be reaped. Statistical analysis applied over the years on TA patterns (Bulkowski 2021) promises clear chances of success.

4.2. The Social Value of HF, Technical, MHP-driven Trading

The rosy picture drawn in the previous section for High-Frequency-technical traders is certainly not always rosy for all. Traditional, or low-frequency, traders do not enjoy the benefits of ultra-fast transactions but they run into the costs HFT generates. HFT reduces volatility during quiet times but may exacerbate it when markets are under stress, that is, exactly when volatility spikes might turn into disasters (Kirilenko et al. 2017). If trading is a zero-sum game, as Pagnotta and Philippon (2018) suggest, then profitable innovations for one side reveal to be losses for the other(s). According to Farmer and Skouras (2012, p.22) “[t]he private value of more relative speed would remain large even though the social value of more speed is negative”, and Budish et al. (2015) assign social optimal value to slow trading, as compared to HFT, a form of trading in which many suffer and only a few win. In this process, the total technology investment costs may exceed the total benefit. This is a crucial point: despite ensuring abnormal profits for HF traders to the detriment of slow traders, whether total wealth is increased or decreased makes a big theoretical difference. Given a certain amount of extra profit for fast traders, if total wealth increases, some kind of just resource assignment can be thought of via a mechanism such as the Tobin tax. A Tobin tax is a fiscal imposition designed to hit speculative flows of money and since HF transactions would very likely fall within its relevance, much discussion has flourished about it. On the other side, if total wealth were diminishing face to increased profits of ultra-fast traders, social justifications of HFT would fade away. As Farmer and Skouras (2012, p.22) remark: “many individual investors are harmed by market speed, each by a relatively small amount which

however is much larger than the benefits from speed which are extracted by just a few institutions”. Nevertheless, the speed race keeps moving ahead. NASDAQ and Chicago Mercantile Exchange, which in 2014 provided market data with millisecond granularity, after a few years moved to nanosecond granularity: a clear sign of increased care for HF clients’ requests. Menkveld (2014) reports some of the arguments in favor and against HFT. Its defendants claim that the whole market benefits from quicker reflection of news into prices, making markets more efficient. On the other side, the author finds that HF firms overinvest in technology concerning the social optimum and he is sceptical about the social value of timely information efficiency. In this sense, he aligns himself with Paul Krugman, the 2008 Economics Nobel Prize winner, who declared:

“It’s hard to imagine a better illustration (of social uselessness) than high-frequency trading. The stock market is supposed to allocate capital to its most productive uses, for example by helping companies with good ideas raise money. But it’s hard to see how traders who place their orders one-thirtieth of a second faster than anyone else do anything to improve that social function... we’ve become a society in which the big bucks go to bad actors, a society that lavishly rewards those that make us poorer.” P. Krugman, New York Times, 2/8/2009

Joseph Stiglitz, 2001 Economics Nobel Prize winner, refers to “a general theorem (using general results in the theory of statistical decision making) suggesting that the costs of slight improvements in information may outweigh the benefits” (Stiglitz 2014, p.5) and even that, by accessing information before others, “has resulted in an unlevel playing field, allowing [fast traders] to garner rents for themselves at the expense of others” (Stiglitz, 2014, p.13). Hirschey (2021) also finds that HFT impose traditional investors with higher trading costs.

5. Conclusions

The purpose of this paper was to compare the Monty Hall problem to information imbalance in the stock market and demonstrate that speedy information leads to above-average performance. Indeed, the Problem bears a profound resemblance to how modern financial markets work. Its counter-intuitive Bayesian solution adapts easily to the choices made every day, hours, seconds, and fractions thereof by informed, technical, and high-frequency traders. In both situations, a subject makes a decision and, based on market information, she/he can either confirm or change such a decision, much like the MHP. The higher complexity of financial markets with respect to a TV show resides in the very large amount of information that must be taken into account and interaction with a very large number of competitors. Choice in financial markets is given by the rather large number of chart patterns provided by Technical Analysis. Assuming a trader is sufficiently experienced to consistently pick up the pattern that fits the price profile best, she is more or less guaranteed to enjoy a reasonably low break-even failure rate. It means that, over a sufficiently large number of pattern applications, she can hope to make a loss (not breaking even) only a very low number of times compared to the total. That should be enough to avoid overall losses and, quite likely, to make a gain at the end of the day. Even if break-even failure rates were much higher than those shown by Bulkowski (2021), experienced technical traders could expect to close a trading day successfully most of the time. However, information alone is not enough, no matter how good; it needs to be coupled with ultra-high speed. Speed of execution has been a critical success factor ever since in financial markets. Executing trades quickly rather than slowly, presents two advantages: the near guarantee to get first to a profitable deal and the possibility to executing many more deals per time unit. This paper demonstrated that combining information and execution speed enormously increases the chances of profitable trading. Whereas most practitioners recognize the advantages of HFT, academia is not so clear-cut, and some scholars even think HFT provides no advantage at all.

Therefore, a definitive mathematical demonstration, as shown above, could help to settle the matter. The results could be useful to market regulators and policy makers. Indeed, making speedy use of information provided by chart patterns, although a good way to achieve financial success for the few, may not be the most desirable path for the financial community at large, market regulators and the whole economy.

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Table 1: Break-even failure rate and average price movements (rise in bull market and decline in bear market) in case of upward breakouts

	B-E failure rate		Average rise/decline	
	Bull market	Bear market	Bull market	Bear market
Broadening Bottom	10%	9%	27%	21%
Right-Angled and Ascending	11%	11%	29%	15%
Right-Angled and Descending	19%	6%	28%	23%
Broadening Tops	15%	11%	29%	24%
Broadening Wedges Ascending	2%	0%	38%	18%
Broadening Wedges Descending	6%	11%	33%	24%
Bump-and-Run Reversal Bottoms	2%	1%	38%	31%
Cup with Handle	5%	7%	34%	23%
Diamond Bottoms	4%	3%	36%	36%
Diamond Tops	10%	0%	27%	33%
Double Bottoms Adam & Adam	5%	7%	35%	24%
Double Bottoms Adam & Eve	5%	4%	37%	33%
Double Bottoms Eve & Adam	4%	8%	35%	23%
Double Bottoms Eve & Eve	4%	7%	40%	24%
Flags	4%	3%	23%	17%
Flags High and Tight	0%	0%	69%	42%
Head-and-Shoulders Bottoms	3%	4%	38%	30%
Head-and-Shoulders Bottoms Complex	4%	3%	39%	31%
Horn Bottoms	9%	7%	35%	27%
Island Reversals	18%	10%	23%	21%
Islands Long	11%	4%	31%	25%
Pennants	2%	2%	25%	21%
Pipe Bottoms	5%	4%	45%	32%
Rectangles Bottoms	10%	11%	46%	24%
Rectangles Tops	9%	16%	39%	20%
Rounding Bottoms	5%	5%	43%	31%
Rounding Tops	8%	16%	37%	19%
Scallops, Ascending	10%	16%	31%	19%
Scallops Ascending and Inverted	4%	7%	43%	26%
Scallops, Descending	22%	20%	22%	20%
Three Raising Valleys	5%	9%	41%	22%
Triangles, Ascending	13%	12%	35%	30%
Triangles, Descending	7%	9%	47%	27%
Triangles Symmetrical	9%	7%	31%	26%
Triple Bottoms	4%	8%	37%	23%
Wedges, Falling	11%	11%	32%	26%
Wedges, Rising	8%	14%	28%	17%
Average	7.64%	7.65%	35.30%	25.08%
Standard deviation	5.07%	4.92%	8.65%	5.85%

(Source: Bulkowski, 2021)

Table 2. Break-even failure rate and average price movements (rise in bull market and decline in bear market) in case of downward breakouts

	B-E failure rate		Average rise/decline		
	Bull market	Bear market	Bull market	Bear market	
Downward Breakouts	Broadening Bottom	16%	9%	15%	18%
	Right-Angled and Ascending	20%	8%	15%	22%
	Right-Angled and Descending	14%	4%	15%	23%
	Broadening Tops	18%	3%	15%	20%
	Broadening Wedges Ascending	11%	14%	17%	21%
	Broadening Wedges Descending	9%	2%	20%	25%
	Bump-and-Run Reversal Tops	5%	1%	19%	27%
	Cup with Handle Inverted	11%	2%	16%	26%
	Diamond Bottoms	10%	9%	21%	44%
	Diamond Tops	6%	4%	21%	24%
	Double Tops Adam & Adam	8%	11%	19%	19%
	Double Tops Adam & Eve	14%	7%	18%	22%
	Double Tops Eve & Adam	13%	5%	15%	24%
	Double Tops Eve & Eve	11%	2%	18%	25%
	Flags	2%	8%	16%	25%
	Head-and-Shoulders Tops	4%	1%	22%	29%
	Head-and-Shoulders Tops				
	Complex	4%	1%	23%	27%
	Horn Tops	7%	2%	21%	22%
	Island Reversals	17%	5%	17%	23%
	Islands Long	5%	2%	22%	26%
	Pennants	4%	0%	19%	25%
	Pipe Tops	11%	2%	20%	27%
	Rectangles Bottoms	16%	4%	14%	25%
	Rectangles Tops	11%	9%	17%	21%
	Rounding Tops	12%	9%	19%	23%
	Scallops, Ascending	27%	14%	14%	19%
	Scallops, Descending	22%	20%	22%	20%
	Scallops Descending and Inverted	10%	5%	18%	23%
	Three Falling Peaks	12%	4%	17%	24%
	Triangles Ascending	11%	3%	19%	24%
	Triangles Descending	16%	11%	16%	25%
	Triangles Symmetrical	13%	9%	17%	19%
	Triple Tops	10%	5%	19%	24%
	Wedges Falling	15%	6%	15%	24%
	Wedges Rising	24%	15%	14%	20%
	Average	11.97%	6.17%	17.86%	23.86%
	Standard deviation	5.83%	4.71%	2.61%	4.40%

(Source: Bulkowski, 2021)

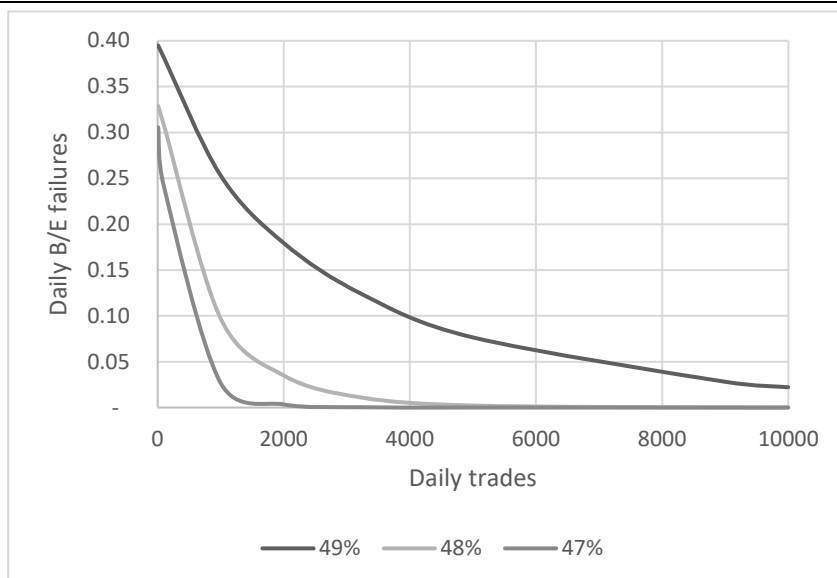


Figure 1 Decrease of daily break-even failures as a function of daily trades (Source: author's elaboration)

Table 3. Failures and failure frequency per number of daily trades with B-E failure rate = 49%

Break-even failure rate = 49%			
Daily trades	Daily failures	Failure frequency	
10	0.353	88.15	per year
100	0.382	95.48	per year
1000	0.253	63.31	per year
10000	0.022	5.55	per year

(Source: author's elaboration)

Table 4. Failures and failure frequency per number of daily trades with B-E failure rate = 48%

Break-even failure rate = 48%			
Daily trades	Daily failures	Failure frequency	
10	0.329	82.21	per year
100	0.308	77.04	per year
1000	0.097	24.31	per year
10000	3.014E-05	1	every 133 years

(Source: author's elaboration)

Table 5. Failures and failure frequency per number of daily trades with B-E failure rate = 47%

Break-even failure rate = 47%			
Daily trades	Daily failures	Failure frequency	
10	0.306	76.42	per year
100	0.241	60.34	per year
1000	0.027	6.68	per year
10000	8.963E-10	1	every 4,450,000 years

(Source: author's elaboration)

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