Technical Analysis for Profitable Trading

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Abstract

This dissertation contributes to the current literature regarding the effectiveness of technical analysis as a trading tool and its usefulness for holding period return predictability.

Using exclusively technical analysis patterns as input features, the author shows substantial minute holding period return predictability for the EUR/USD, USD/JPY and GBP/CHF exchange rates, during some periods in the first decade of the 21st century. The implemented investment strategies are based on a rolling window of logistic regression algorithms with an adjusted decision threshold. The models' observed predictability was capable of being materialized in an intraday technical analysis trading strategy that would've produced wealth out-of-sample and after transaction costs.

The confidence, predictability and profitability capacity of the models appears to be declining and may no longer exist.

Title: Technical Analysis for Profitable Trading

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Keywords: Technical analysis, Machine learning, Logistic regression, Holding period return, Forex, Profitable, Trading, Strategy, Out-of-sample

Resumo

Esta dissertação contribui para estudos recentes relativos à eficácia de análise técnica como uma ferramenta de investimento e a sua utilidade na previsão de retornos do período de retenção.

Utilizando exclusivamente padrões de análise técnica como variáveis independentes, o autor mostra previsibilidade substancial nos retornos de período de retenção ao minuto, para as taxas de câmbio EUR/USD, USD/JPY e GBP/CHF, durante alguns períodos da primeira década do século XXI. As estratégias de investimento implementadas são baseadas numa janela deslizante, que utiliza algoritmos de regressões logísticas com um limite de decisão ajustado. A previsibilidade de retornos observada pelos modelos foi materializada numa estratégia intradiária que teria produzido riqueza para o investidor, fora de amostra e após custos de transação.

A confiança, capacidade de previsão e lucratividade dos modelos aparenta ter vindo a dissipar-se, podendo já não existir.

Título: Technical Analysis for Profitable Trading

Autor: Duarte da Fonseca e Costa Lopes Pombo

Palavras-chave: Análise técnica, Aprendizagem máquina, Regressão logística, Retornos do período de retenção, Forex, Lucro, Investimento, Estratégia, Fora de amostra

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ABREVIATION	DEFINITION
AUC	Area Under the Curve
BBOT	Broadening Bottoms
BPS / bps	Basis Points
BTOPS	Broadening Tops
CFD	Contract For Difference
CIP	Covered Interest rate Parity
DBOT	Double Bottoms
DJIA	Dow Jones Industrial Average
DTOP	Double Tops
ECB	European Central Bank
FA	Fundamental Analysis
FED	Federal Reserve
FN	False Negatives
FOREX / Forex	Foreign Exchange
FP	False Positives
FRED	Federal Reserve Economic Data
HPR	Holding Period Return
HS	Head and Shoulders
IHS	Inverse Head and Shoulders
IPO	Initial Public Offering
OHLC	Open High Low Close
OOS	Out-Of-Sample
QE	Quantitative Easing
RBOT	Rectangle Bottoms
RTOP	Rectangle Tops
TA	Technical Analysis
TA-LIB	Technical Analysis Library
TBOT	Triangle Bottoms
TC	Transaction Costs
TN	True Negatives
TP	True Positives
TTOPS	Triangle Tops

1 Introduction

Technical Analysis (TA) is a method in which investors attempt to forecast price movements using past price information, volume and/or open interest, ignoring economic or fundamental analysis.

Although widely used, TA is a very controversial investment tool. The objective of this study is to assist in the reduction of the existing dissensus, by studying if some TA patterns are useful for predicting next minute Holding Period Return (HPR).

There are numerous studies on TA indicators and patterns individually, but research regarding strategies that implement them in a combined way (which better represent how technical analysts typically invest) are not as common.

This study implements an innovative strategy based on a rolling window of logistic regressions with Threshold-Moving. The results present periods where the TA explanatory variables could be used for minute HPR predictability and would've provided highly profitable trading for the investor, even after Transaction Costs (TC). This strategy performed remarkably well across different currency exchange rates during a short period in the first decade of the 21st century. The models' precision and recall declined substantially over time, indicating that they are struggling to find a linear relationship between the occurrence of the technical indicators and HPR predictability during the second decade of the 21st century. This eventually causes the strategies to lose all their capacity to deliver positive returns after TC.[1] The loss in HPR predictability is consistent with the results observed in several other studies (e.g., Marsh, 2000).

Nevertheless, using only TA patterns and a very basic machine learning linear classifier, this study observes substantial HPR predictability in three currency exchange rates for some periods during the first decade of the 21st century. This gives hope to more sophisticated machine learning models and provides evidence that technical patterns, if correctly employed, were useful for implementing profitable intraday foreign exchange investment decisions.

[1] This dissertation does not attempt to construct a strategy using the most "human-like" pattern recognition algorithms, neither attempts to develop the best possible machine learning models or the most lucrative TA trading strategy (this would require an unobtainable number of resources). Detecting HPR predictability and successfully implementing a profitable trading strategy (after transaction costs), using as inputs only TA indicators is sufficient.

1.1 Literature Review

Academics have been very skeptical of TA while quickly adopting Fundamental Analysis (FA). Quoting from Lo et al. (2000), "*It has been argued that the difference between fundamental analysis and technical analysis is not unlike the difference between astronomy and astrology*" (p. 1705).

It is comprehensible that FA was widely adopted due to its intrinsic logical nature. If we can estimate the true value of an asset, it makes sense that when bought below fair value, the price should eventually adjust and yield a positive return to the holder.

It is harder to debate that the adoption of TA was born from a similar logical nature. Instead, its workings are typically compared to behavioral finance (Lu et al. 2012). Technical patterns may be reflecting investors' emotions and irrationality. Therefore, its usage could capacitate the detection and profiting from these emotional responses. Nison (1991) shares an even stronger opinion, "*Technical analysis provides the only mechanism to measure the irrational (emotional) component present in all markets*" (p. 9).

On the other hand, as stated by Hirshleifer et al. (2016) "*The popularity of technical trading systems may come in part from superstitious faith in the power of numerical patterns*" (p. 3, footnote #4).[2]

TA also seems to attract the attention of "investment gurus" and inexperienced retail investors. One possible explanation is a shallow learning curve compared to FA. TA has the advantage that it can be used without the need of having any finance or mathematical background.

There are critics of both TA and FA. Malkiel (1999) in his book, A Random Walk Down Wall Street, suggests that stock markets follow a random walk and therefore one cannot consistently outperform the market (by using TA or FA). He also stated, "*It seems very clear that under scientific scrutiny, chartreading must share a pedestal with alchemy*" (p. 159) and "*I have*

[2] Interestingly, Hirshleifer et al. (2016) finds that numerological superstition affects financial decisions in the Chinese IPO market. Stocks are given numerical codes and investors often use them as reference. Numbers such as 2, 6, 8 and 9 are considered lucky because they sound similar to the words "harmony", "good luck", "wealth" and "longevity", while the number 4 is unlucky because it sounds similar to "death". IPOs of stocks with lucky numbers obtained on average 23% higher valuation and subsequently underperformed IPOs of stocks with unlucky numbers.

personally never known a successful technician, but I have seen the wrecks of several unsuccessful ones" (p. 139).

Although TA is still a controversial investment tool, it is widely adopted by both retail and institutional investors.

Taylor & Allen (1992) report that at least 90% of chief foreign exchange dealers based in London in November 1988 place some weight in technical analysis and that "*There is also a skew towards reliance on technical, as opposed to fundamentalist analysis at shorter horizons, which becomes steadily reversed as the length of horizon considered is increased*" (p. 304).

Billingsley & Chance (1996) find that approximately 60% of commodity trading advisors rely on technical trading systems (as cited in Wang et al., 2019). Lui & Mole (1998) reveal that exchange dealers in Hong Kong in February 1995 consider technical analysis more useful than fundamental analysis. According to Menkhoff (2010), 87% of fund managers rely on technical analysis. Etheber (2014) suggests that moving average signals cause strong shifts in the trading activity of a given stock and can induce strong price reactions.

Although the large adoption of TA among investors is evident, academic literature is not certain regarding its usefulness. Several studies challenge the effectiveness of TA as an investment tool.

Allen & Karjalainen (1999) used a genetic algorithm to learn technical trading rules for the S&P 500 index using daily prices from 1928 to 1995 and conclude that these rules do not earn consistent excess returns over a simple buy-and-hold strategy, out-of-sample, and after accounting for transaction costs. Olson (2004) tests profits regarding moving average trading rules and shows that risk-adjusted profits have been declining over time from an average of 3% in the late 1970s and early 1980s to about 0% in the 1990s. Using an extension of the bootstrap methodology, Marshall et al. (2006) find that candlestick trading strategies do not have value for DJIA stocks. Marshall et al. (2008) find that none of the 7846 popular technical trading rules that are tested are profitable after data snooping bias is considered. Abbey & Doukas (2012) show that technical analysis is negatively associated with portfolio performance of currency traders.

Other studies show a more favorable view.

Lo et al. (2000), find that over many U.S. stocks from 1962 to 1996, several technical indicators provide incremental information and may have practical value. Lee et al. (2003) point out that while a contrarian approach (based in TA) is not a viable stand-alone strategy, it may be value-enhancing when employed as an overlay strategy. Zhu & Zhou (2009) analyze the use of moving averages from an asset allocation perspective and reach the conclusion that when stock returns are predictable, technical analysis adds value to commonly used allocation rules that invest fixed proportions of wealth in stocks. Shiu & Lu (2011), conduct a study using data from the Taiwan Stock Exchange between 1998 and 2007 and find that the harami candlestick pattern can obtain information regarding short-term price movements derived from demand and supply in this market. Lu et al. (2012) find that three bullish reversal candlestick patterns were profitable in the Taiwanese stock market from 29th of October 2002 until 31st of December 2008. Hudson & Urquhart (2021) examine technical trading rules in the cryptocurrency markets and find these offer significant predictive power and profitability to investors while also offering substantially higher risk-adjusted returns than the simple buy-and-hold strategy.

2 Data

This dissertation uses minute data of the EUR/USD, USD/JPY and GBP/CHF exchange rates.[3] These currency pairs were chosen due to their high trading volume and popularity. EUR/USD and USD/JPY are the first and second most traded currency pairs. Since 2004, they are consistently presented by the Bank of International Settlements' Triennial Central Bank Survey as the top two traded currency exchange rates (Bank for International Settlements, 2019).[4] The model was also tested in the GBP/CHF currency pair. This was done to assess the predictability and performance of the models in an exchange rate that did not include USD.

However, the inclusion of USD does not seem like a potential cause of systematic bias in the performance of the models. This is because USD/JPY seemed to present an even lower overall monthly correlation to EUR/USD than GBP/CHF (Figure 1 and Figure 2).

[3] This decision was based on the findings of Taylor & Allen (1992) and Gehrig & Menkhoff (2006). The former concluded that investors present a skew towards using technical indicators at shorter time horizons, the latter indicated a seemingly higher presence of technical analysts operating in the forex market than in the commodities or equities.

[4] EUR/USD and USD/JPY made up 24% and 13.2% of daily foreign exchange transactions in April 2019.

Figure 1

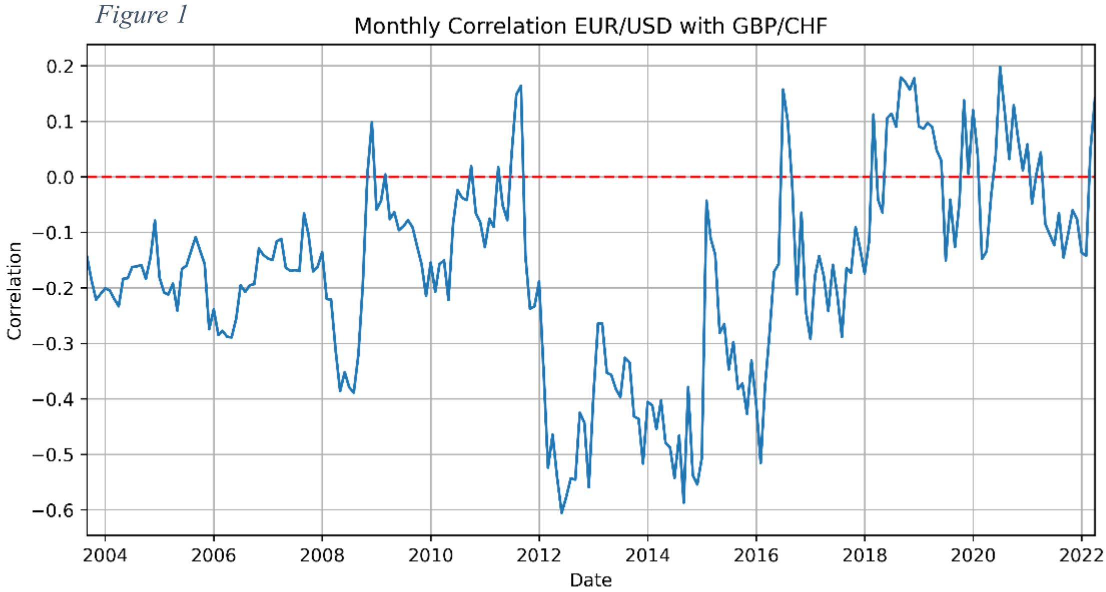
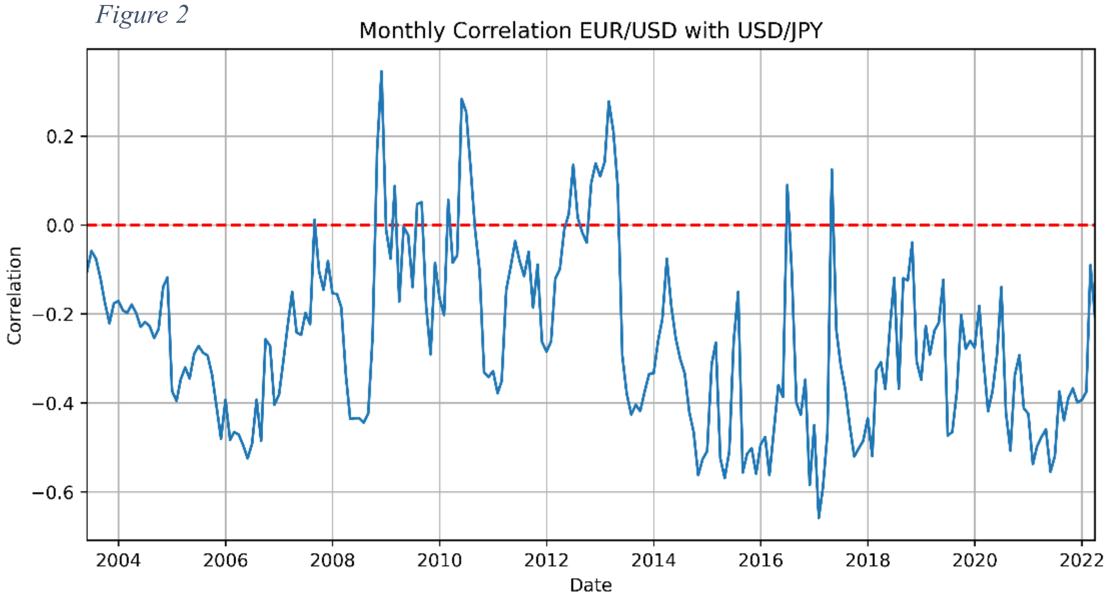


Figure 2



In this dissertation, logistic regressions will attempt to find linear combinations of the technical patterns and use them to explain next period HPR. Since correlation is a measure that expresses the extent of which two variables are linearly related, if the model has excellent performance in a given currency exchange rate, currency pairs that are highly correlated with it, could also inherit this performance. As later presented, the strategies applied in the USD/JPY and GBP/CHF currency exchange rates, showed the highest HPR predictability until 2005. From Figure 1 and Figure 2 we can observe that these periods didn't particularly correlate substantially with EUR/USD (which was the currency pair that the strategy outperformed during a longer time window).

2.1 Descriptive Statistics

Although the data downloaded is more extensive, the prediction window of the model applied to the GBP/CHF Exchange Currency Rate is from 2003-08-20 until 2022-03-04. In Table 1, some descriptive statistics are presented for this period (basis points (bps) = 0.01%).

Average annualized HPR, annualized volatility, Sharpe Ratio, cumulative returns and Evolution of Wealth are defined in Section 3.2.2. The proportional Bid-Ask Spread is defined in Section 3.4.

Table 1

Descriptive Statistics from 2003-08-20 until 2022-03-04			
From	**EUR/USD**	**USD/JPY**	**GBP/CHF**
Number of Observations	6,934,564	6,930,365	6,932,700
% of positive HPR	46.9484%	43.3451%	46.9501%
% of HPR below or equal to 0	53.0516%	56.6549%	53.0499%
% of HPR above 0.6 basis points	26.6210%	26.9370%	28.4818%
% of HPR below or equal to 0.6 basis points	73.3790%	73.0630%	71.5182%
Average Proportional Bid-Ask Spread	0.6152 bps	0.8452 bps	2.2298 bps
Average Annualized HPR	0.4071%	0.4268%	-2.4133%
Annualized Volatility	9.8927%	10.8855%	12.0647%
Sharpe Ratio	0.0411	0.0392	-0.2000
Cumulative Returns	-1.5596%	-3.1160%	-45.1164%
Evolution of Wealth	0.9844	0.9688	0.5488

An important metric to notice in Table 1 is the much higher proportional Bid-Ask spread presented in the GBP/CHF currency exchange rate. This will play a huge role in the outcome of the implemented strategies.

2.2 Dukascopy's Historical Data Feed

The currency exchange rates were retrieved from Dukascopy's Historical Data Feed (with current active link: https://www.dukascopy.com/swiss/english/marketwatch/historical/).

This data source was considered a trustworthy supplier of free intraday Open, High, Low and Close (OHLC) price data.[5] Dukascopy is an online Swiss bank founded in 2004 that provides online, mobile trading, banking, and financial services worldwide (with a focus on foreign exchange, bullion, CFD and binaries).

Although this source appears to be credible, the author recognizes this is not a popular database used amongst academic literature. Even so, this was the source used due to lack of availability of free intraday OHLC forex data.

2.2.1 Data retrieval parameters

The bid and ask OHLC prices were retrieved for all three currency exchange rates. For EUR/USD and USD/JPY, the data range downloaded was from 2003-05-04 until 2022-03-04. The website does not provide such a long time-period for GBP/CHF, therefore, for this currency exchange rate, the downloaded range was from 2003-08-04 until 2022-03-04.

The filter flats was set to "All". This automatically removes the periods in which the underlying currency pair is not being traded due to the forex market being closed (e.g., weekends). The day start time parameter was set to UTC and time to GMT.

As mentioned, the ask and bid data was retrieved (maintaining all other parameters fixed). This will serve to compute the proportional Bid-Ask Spread for each minute and reach a simplified measurement of period TC (explored in Section 3.4).

The total number of observations (periods) downloaded is 7,045,652 for EUR/USD, 7,028,065 for USD/JPY and 6,937,057 for GBP/CHF.

Although the volume amount was chosen to be presented in units, this variable is never used for constructing the desired models.

[5] There are several factors that assisted reaching this conclusion. One of them is the use of this source of data in other scientific papers (e.g., Ivanov & Yan, 2021), another factor was Dukascopy bank's popularity amongst Technical Analysts. Dukascopy was the winner/finalist of several awards, including *2020 Best FX Research* and *2020 Best Technical analysis Platform*. A list of all Dukascopy bank's awards can be found in the following web page: https://www.dukascopy.com/swiss/english/about/awards/).

2.3 Variables of the model

2.3.1 Label (Dependent Variable)

HPR is computed from the ask close price data and is defined as:

$$HPR_t = \frac{Price_t}{Price_{t-1}} - 1 \tag{1}$$

The purpose of this study is to determine if we are capable of detecting HPR_t predictability for the underlying currency exchange rate, using technical analysis patterns that occurred before t.

As explained in Section 3.1, logistic regressions will be used as a machine learning classification algorithm. This entails that the label (or dependent variable) is a dummy variable which assumes the value of 1 when HPR is above a certain threshold and 0 otherwise.

There are two models that will be created and applied as two distinct investment strategies. The label threshold of the first strategy, which will be informally named the "Regular Logistic Regression", will assume the value of 0. This means $Label_t$ will assume the value of 1 if $HPR_t > 0$.

In the second model, which will be named the "Rigorous Logistic Regression", the label threshold will be 0.00006 or 0.6 bps. Therefore, $Label_t$ will assume a value of 1 if $(HPR_t \times 10{,}000) > 0.6$.

Another distinctive aspect of the Rigorous Logistic Regression model will be threshold moving. This will be further detailed in sections 3.1 and 4.2.

2.3.2 Inputs of the model (Explanatory Variables)

The explanatory variables (also called features or inputs) used in both Logistic Regression strategies are created solely from technical analysis patterns. These model features are gathered with the assistance of two different sources: The Technical Analysis Library (TA-Lib) and technical pattern definitions retrieved from Lo et al. (2000) converted into code.

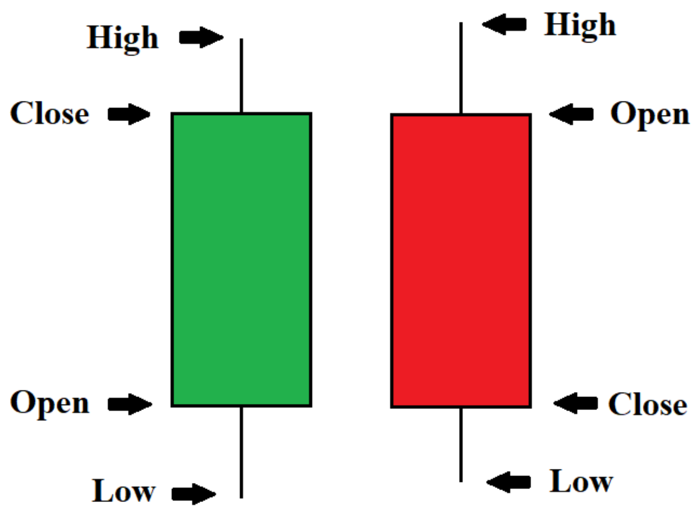
As mentioned in the previous section, the purpose of this study is to assess HPR_t predictability of the underlying currency exchange rate, using technical analysis patterns that occurred before period t. It is highly challenging to develop technical analysis algorithms that perform pattern recognition like a human technical trader. As we shall see further, the recognition algorithms inspired by the definitions presented in Lo et al. (2000) tend to detect too many patterns.

This is not a significant problem. Since all information used as inputs is constructed from past prices, this paper is still evaluating HPR predictability using TA. The objective of this dissertation is not to have the finest tuned technical analysis model, neither is to construct the best possible technical analysis strategy. The detection of HPR predictability using only technical indicators as explanatory variables, and the successful implementation of a profitable trading strategy (after TC) is considered sufficient.

2.3.2.1 TA-Lib

Technical traders tend to rely heavily on candlestick pattern recognition for making investment decisions. In this study, each candlestick corresponds to 1 minute and is constructed from the open, high, low and close prices in the following manner (Figure 3).

Figure 3



Researchers' present different beliefs regarding candlestick pattern's usefulness when it comes to implementing investment decisions.[6] Nevertheless, candlestick chart-reading is very popular amongst technical traders.

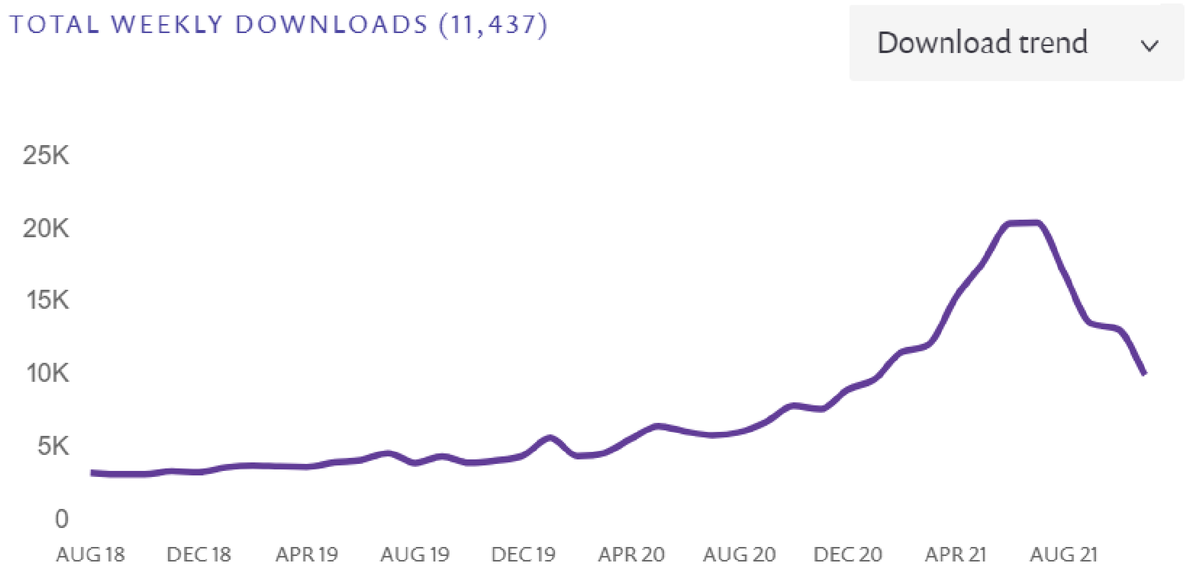
TA-Lib is a widely used technical analysis library, used by trading software developers that includes 200 indicators and 61 candlestick pattern recognition tools. This was the source of all candlestick patterns used in this dissertation.

TA-Lib has an Open-source API for C/C++, Java, Perl, Python and is constantly being updated by its developers and the community. This project will use the 61 candlestick pattern recognition tools presented in a Python wrapper for TA-Lib based in Cython.[7]

The list of the 61 candlestick pattern recognition tools is presented in the appendix (Table I).

TA-Lib appears to be a credible source of pattern recognition algorithms. The Python wrapper used is very popular and well maintained. It has 7 years of existence, is regularly updated, and has 17 contributors at the time of writing. It is also highly popular amongst technical algorithmic traders. *Snyk package health analysis* scores TA-Lib popularity as "Popular" and presents the following graph (Figure 4) of average weekly downloads for the last 6 weeks.[8]

Figure 4 – source: Snyk Advisor(snyk.io); Current active url: https://snyk.io/advisor/python/ta-lib



[6] Using examples from the Literature Review section, Shiu & Lu (2011) and Lu et al. (2012) find favorable results, while Marshall et al. (2006) find unfavorable.
[7] Developed by John Benediktsson (mrjbq7) and other contributors, current active link: https://mrjbq7.github.io/ta-lib/
[8] As seen in Snyk Advisor, a website that evaluates quality of Python packages. Current active link: https://snyk.io/advisor/python/ta-lib

TA-Lib was also used in several scientific papers/books with the purpose of constructing trading strategies, for e.g., Duvinage et al. (2013), Xu & Keselj (2019) and Gong et al. (2022).

2.3.2.1.1 Candlestick Pattern identification process

When calling any of the candlestick pattern recognition functions, it is necessary to provide as input the open, high, low and close prices. These functions will return a vector with length equal to the number of time-periods given and a value different than 0 (a signal) when the candlestick pattern is observed.

The entries of the returned vector will assume the value of -200 when there is a bearish confirmation (for bearish patterns), -100 when a bearish pattern occurs, 0 when the pattern is not observed, 100 when a bullish pattern occurs and 200 when there is a bullish confirmation signal. By construction, the signal is always presented in the date of the last candlestick that belongs to the pattern.

Figure 5 presents an example of a Three Black Crows candlestick pattern that was presented as a -100 signal at 05 May 2003, at 21:48:00 in the EUR/USD currency pair.

Figure 5 – source: Dukascopy's Historical Datafeed: https://www.dukascopy.com/swiss/english/marketwatch/historical/

Naturally, to test the candlestick patterns' ability to predict HPR Out-Of-Sample (OOS), it is necessary to lag these Candlestick pattern features by one observation (using therefore $Candlestick\ Pattern_{t-1}$ to predict HPR_t).

Using Figure 5 as an example, the model would only "know" the existence of the Three Black Crows bearish pattern at the beginning of the period 2003-05-05 at 21:49:00. Therefore, only then the model can implement a trade based on it.

After retrieving all desired 61 candlestick pattern recognition vectors, these were transformed into dummy variables.

The resulting dummy variables were identified with the name of the pattern, followed by "_StrongShort" when a -200 was observed, a "_short" if a -100 was observed, a "_hold" if a 0 was observed, a "_long" if a 100 was observed and a "_StrongLong" if a 200 was observed. One of the dummies for each candlestick pattern was removed to avoid perfect multicollinearity problems. As such, the initial 61 candlestick patterns were converted into 92 dummy variables.

Below (Figure 6) is a slice of the Explanatory variable table containing the candlestick patterns for the EUR/USD data to serve as an illustrative example.

Figure 6

date	TwoCrows_short	ThreeBlackCrows_short	ThreeInsideUpDown_short	ThreeInsideUpDown_hold	ThreeLineStrike_short	ThreeLineStri
2003-05-05 21:47:00	0	0	0	1	0	
2003-05-05 21:48:00	0	0	0	1	0	
2003-05-05 21:49:00	0	1	0	1	0	
2003-05-05 21:50:00	0	0	0	1	0	
2003-05-05 21:51:00	0	0	0	1	0	

Evidenced by the red circle, is the ThreeBlackCrows_short pattern presented in Figure 5 but already properly lagged. Notice the model will only recognize the pattern at 21:49:00 (Figure 6) while TA-Lib presented it as occurring at 21:48:00 (Figure 5).

2.3.2.2 Definitions from Lo et al. (2000)

In Lo et al. (2000), the authors define a total of 10 technical patterns. This dissertation will use the subsequent eight: Head and Shoulders (HS), Inverse Head and Shoulders (IHS), Broadening Tops (BTOPS), Broadening Bottoms (BBOT), Triangle Tops (TTOPS), Triangle Bottoms (TBOT), Rectangle Tops (RTOP) and Rectangle Bottoms (RBOT). The definitions of the patterns used are presented in the appendix, Figure I. The patterns “DTOP” and “DBOT” were excluded from this study because the definitions required that some local extrema occurred at least 22 trading days apart.

All technical patterns used are characterized by a sequence of five consecutive local extrema $E_1,\ldots,E_5$. To detect them, Lo et al. (2000) used a nonparametric kernel regression. When using this approach, the pattern recognition algorithm will ignore extrema that are “too local”. The simpler and computationally less exhaustive process used in this dissertation, follows directly the definitions mentioned (appendix, Figure I), using only consecutive local extrema and identifies them directly from the raw close price data. This was the procedure chosen due to the massive number of observations this study was conducted on, and lack of computational power.

Using this method, the pattern definitions (appendix, Figure I) were converted into code and 8 functions were developed that, given as input an array of time-series close price data, will return a dummy variable that is equal to 1 when the desired technical pattern is observed and 0 otherwise (e.g., Figure 8). At the end of this procedure, the function automatically lags this dummy array by 2 periods.

Since these technical patterns are characterized by consecutive local maxima and minima, it is necessary to lag by 2 periods. The reason is very simple: if the technical pattern always ends in a local maximum (minimum) and the author were to make the mistake of lagging the array only by 1 period, excess in-sample information would be included in the model. This is because the model will always identify the pattern in a period that is not going to be a local maximum (minimum), and therefore will always observe a negative (positive) HPR.

In other words: To know that the observed price is a maximum (minimum), the investor must have information regarding the following period. To conduct OOS tests, it is therefore required to lag these explanatory variables by 2 periods.

To increase analysis awareness and confirm process accuracy, the functions developed are also capable of retrieving a table that identifies exactly when each pattern is observed, as well as the prices and period of $E_1, \ldots, E_5$.

Figure 7 presents a slice of this table for the HS technical patterns captured in the EUR/USD currency pair.

Figure 7

	E1 date	E2 date	E3 date	E4 date	E5 date	E1 price	E2 price	E3 price	E4 price	E5 price
0	2003-05-04 21:10:00	2003-05-04 21:12:00	2003-05-04 21:14:00	2003-05-04 21:16:00	2003-05-04 21:17:00	1.12314	1.12313	1.12318	1.12316	1.12307
1	2003-05-04 21:23:00	2003-05-04 21:24:00	2003-05-04 21:25:00	2003-05-04 21:26:00	2003-05-04 21:27:00	1.12307	1.12321	1.12314	1.12316	1.12310
2	2003-05-04 21:37:00	2003-05-04 21:39:00	2003-05-04 21:41:00	2003-05-04 21:44:00	2003-05-04 21:45:00	1.12306	1.12307	1.12320	1.12315	1.12305
3	2003-05-04 21:52:00	2003-05-04 21:53:00	2003-05-04 21:55:00	2003-05-04 21:56:00	2003-05-04 21:57:00	1.12305	1.12308	1.12308	1.12309	1.12304
4	2003-05-04 21:57:00	2003-05-04 21:58:00	2003-05-04 21:59:00	2003-05-04 22:04:00	2003-05-04 22:05:00	1.12304	1.12309	1.12307	1.12274	1.12273
...	...	...	...	...	...	...	...	...	...	...
408636	2022-03-04 20:31:00	2022-03-04 20:32:00	2022-03-04 20:33:00	2022-03-04 20:34:00	2022-03-04 20:35:00	1.09248	1.09253	1.09250	1.09251	1.09224
408637	2022-03-04 20:40:00	2022-03-04 20:42:00	2022-03-04 20:46:00	2022-03-04 20:49:00	2022-03-04 20:53:00	1.09236	1.09262	1.09267	1.09229	1.09239
408638	2022-03-04 20:53:00	2022-03-04 20:54:00	2022-03-04 20:59:00	2022-03-04 21:00:00	2022-03-04 21:01:00	1.09239	1.09240	1.09335	1.09347	1.09325
408639	2022-03-04 21:16:00	2022-03-04 21:17:00	2022-03-04 21:18:00	2022-03-04 21:24:00	2022-03-04 21:28:00	1.09322	1.09330	1.09323	1.09310	1.09293
408640	2022-03-04 21:45:00	2022-03-04 21:46:00	2022-03-04 21:49:00	2022-03-04 21:52:00	2022-03-04 21:53:00	1.09363	1.09369	1.09388	1.09368	1.09328

408641 rows × 10 columns

Figure 8 presents a slice of the HS dummy variable array outputted by the function, for the same currency pair as in Figure 7.

Figure 8

	date	HS
14	2003-05-04 21:17:00	0
15	2003-05-04 21:18:00	0
16	2003-05-04 21:19:00	1
17	2003-05-04 21:20:00	0
18	2003-05-04 21:21:00	0
19	2003-05-04 21:22:00	0

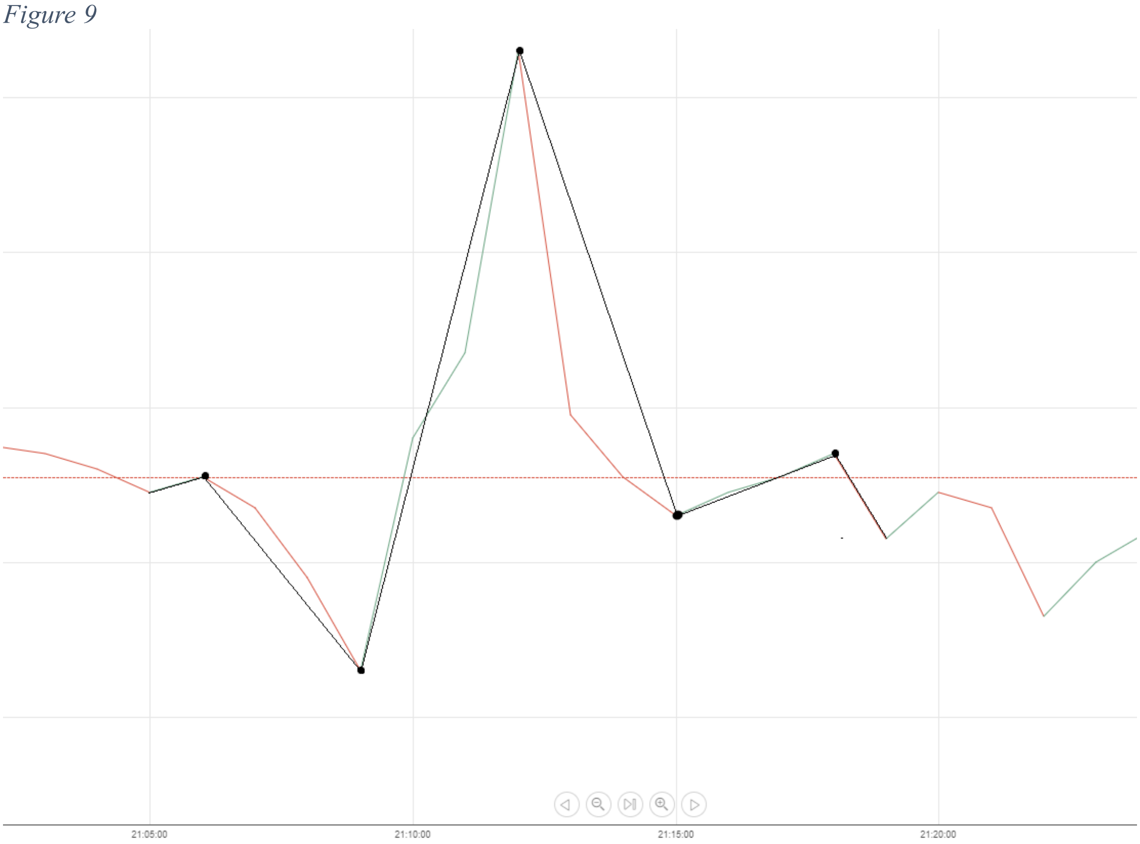
As presented in Figure 7, the first observed HS for the EUR/USD currency pair has its last local extrema (E_5) at 2003-05-04 21:17:00 but, like observed in Figure 8, the technical pattern is only inserted as an input in the model at 21:19:00 (2 periods after) to avoid in-sample bias.

As stated before, the method used for pattern recognition is a simplistic and computationally less exhaustive approach than the one used in Lo et al. (2000). One important limitation of using this process is the fact that it identifies too many extrema and therefore, technical patterns (e.g., as seen in Figure 7, in the EUR/USD time-series data, it identified 408,641 HS patterns in a sample size of 7,045,652 periods). This results in the function sometimes also recognizing patterns that do not appear visually as the kind of pattern a typical technical analyst would detect.

Even so, some technical patterns identified when applying the above-mentioned process, often presented HPR explanatory capacity, being chosen several times by the Feature Selection Model (defined in Section 3.3.1).[9]

Figure 9 shows an example of a HS pattern detected in the USD/JPY currency pair. It is questionable if a typical technical analyst would consider this as a tradable pattern.

Figure 9



It is also important to mention that Lo et al. (2000) study was conducted in the Equity Markets and using daily data. This could reduce the applicability of the definitions used by these authors

[9] From Table III and Table IV presented in the appendix, we can observe that some of these patterns constructed from Lo et al. (2000) were involved in predictions with very large confidence (the models outputted probabilities above 90%), this further validates the usefulness of these definitions when it comes to HPR predictability.

to this study and exacerbate the mentioned aspect of some identified patterns being unrecognized if analyzed by human technical analysts.

3 Methodology

Given all 92 TA-Lib candlestick explanatory variables and the 8 technical indicators constructed from Lo et al. (2000), the author obtained a total of 100 explanatory variables to use in the model as prediction for OOS HPR.

3.1 Logistic Regression

The two proposed models are based in a rolling window of Logistic Regressions.

Logistic Regressions are commonly used supervised Machine Learning algorithms for binary classification. These models predict the dependent variable as either a success (a one) or a failure (a zero) based on a set of explanatory variables and a decision threshold. The logistic function (Equation 2) will collapse the output of a linear regression to a value between 0 and 1. This value is often interpreted as the probability or confidence the model has when predicting.

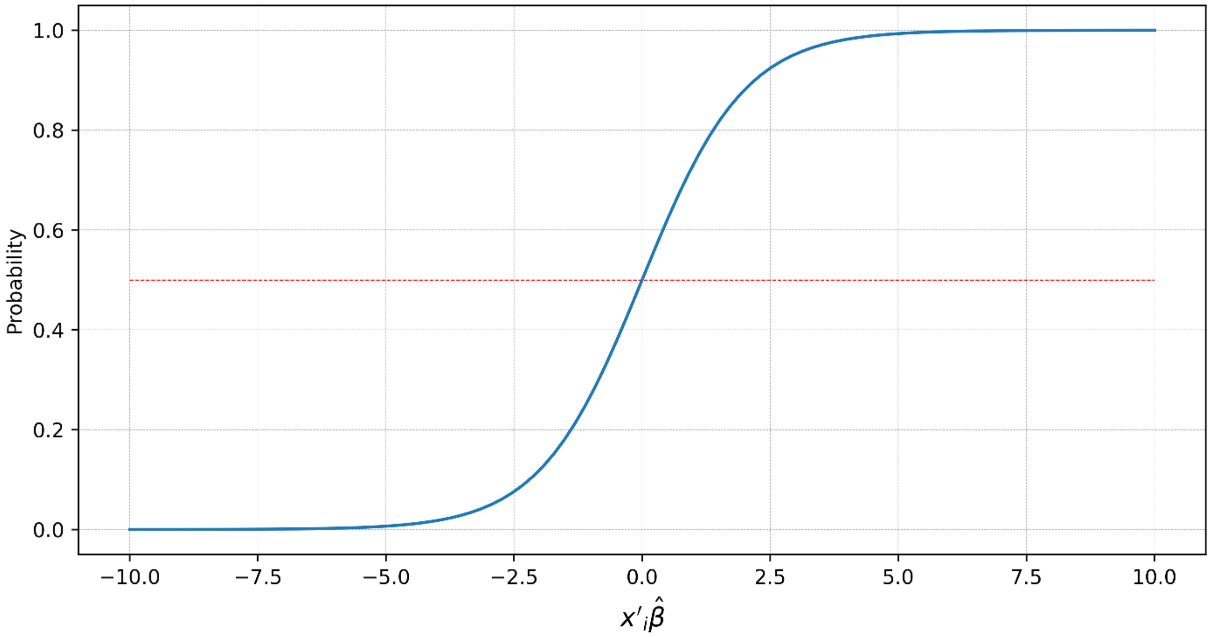
$$Probability_i = \frac{1}{1 + e^{-(x'_i \beta + u_i)}} \tag{2}$$

Where $x'_i\beta + u_i$ is a linear regression ($\beta_1 + \beta_2 x_{2i} + \cdots + \beta_k x_{ki} + u_i$).

the x'_i is a $(1 \times k)$ vector comprised of the explanatory variables (inputs) for period i.

It is standard practice to set the decision threshold probability at 50%. This means that, if based on the given inputs, the logistic function outputs a value above this threshold, the model classifies the dependent variable as a success (outputs the value of 1). Using Figure 10 as an example, if the linear regression output $x'_i\hat{\beta}$ assumed a value above 0, with the decision threshold set to 50%, the model would predict the dependent variable to take the value of 1. [10]

Figure 10 – An example of a logistic regression. Outputted values above the decision threshold (red dotted line) would be classified as 1



Threshold-Moving is the process of shifting the decision threshold to accommodate the objectives of the model. A higher decision threshold creates a more "rigorous" model since it only forecasts the label as a success when it perceives a higher certainty (or probability).

If the model employed in this dissertation outputs a prediction of 1, it is anticipating that the investor is going to experience HPR above a certain threshold and therefore the investment strategy is to have a weight of 100% in the underlying currency exchange rate.

If the model outputs a prediction of 0, it is stating that the investor is not going to experience HPR above a certain threshold and therefore the strategy is to not be invested (if the agent is long, he/she must sell its position and sustain transaction costs).

The main advantage of using logistic regressions in this empirical work, comes from its fast training speed and simplicity of implementation. Logistic regressions, not only provide a measure of how appropriate an explanatory variable is in predicting a label (through the absolute value of its corresponding coefficient), but also indicate the direction of association (if

[10] $\hat{\beta}$ is a $(k \times 1)$ vector comprised of the already trained parameters associated with the explanatory variables.

it has a positive or negative impact in the classification process). These models also have the advantage of a very natural and intuitive probabilistic view of class predictions.

There are several limitations of using logistic regressions. The most evident is the fact it cannot solve non-linear problems due to its linear decision surface. Complex non-linear relationships may often be needed to explain highly complex series such as intraday price fluctuations. More powerful algorithms such as Long Short-Term Memory Recurrent Neural Networks can easily outperform Logistic Regression algorithms and are suitable for time-series data. The large number of observations used, and the need of much superior computational requirements was the deterrent from employing these deep learning algorithms.

Logistic regressions can also suffer from multicollinearity problems when the explanatory variables are highly correlated among each other. This impacts not only the conditional variance of the regression coefficients, but also the predictability capacity of the model. Similar to the regular ordinary least squares regression models, having dummy explanatory variables with almost all values equal to 0 or to 1, will cause these to be highly correlated with the regressor associated with the constant parameter β_1, this can cause multicollinearity problems.[11] However, multicollinearity will not be a substantial problem in this study, this is because the model will only implement a long position when sufficient confidence is observed and the feature selection model also helps to mitigate these problems.[12]

3.2 Performance Metrics

3.2.1 Machine Learning Performance Metrics

The predictability capacity of a machine learning model can be evaluated in several ways. The performance metrics used to quantify this predictability should be selected according to the reality of the underlying problem/study and must be adapted to fit the research question. An

[11] The analogous situation for this study would be to have one or more technical patterns with very few observations.

[12] The feature selection model is defined in Section 3.3.1. This model will mitigate multicollinearity problems because it will only choose the top 5 features, amongst the 100 available, that were observed to have more explanatory power over HPR. The probability of the model choosing, amongst 100 features, a technical pattern that is rarely detected is considerably low.

effective and succinct way to analyze model performance of a classification algorithm is to present a confusion matrix. A confusion matrix is a manner of presenting a summary of prediction results of a classification problem. This procedure summarizes the performance of a classification algorithm by providing information regarding True Positives, False Positives, True Negatives and False Negatives.

Assuming a label that takes the value of 1 when an event occurs and 0 when it does not:

The True Positives (TP) amount is the number of correctly predicted events by the model.

The False Positives (FP) is the number of events that the model predicted but didn't materialize.

True Negatives (TN) is the total number of occasions the model correctly predicted that the event was not going to occur.

False Negatives (FN) is the total number of occasions the model predicted the event was not going to occur, but it did.

From a confusion matrix, it is possible to construct several performance indicators. The ones that seem best fitted to evaluate the relevance of the results in this study are:

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \tag{3}$$

In the specific case of this dissertation, precision can be interpreted as, when the model predicted the agent should've taken a long position, what was the fraction of observed positive HPR.

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} \tag{4}$$

In the specific case of this dissertation, Recall can be interpreted as, amongst all positive HPR observed, what was the ratio of these detected by the model.

$$Accuracy = \frac{True\ Positives + True\ Negatives}{True\ Positives + False\ Negatives + True\ Negatives + False\ Positives} \quad (5)$$

Accuracy represents the fraction of predictions the model was correct.

As it is detailed in Section 4, the training label for the "Regular Logistic Regression model" is an array that assumes the value of 1 when HPR is above 0% and 0 otherwise. The "Rigorous Logistic Regression model" training label will have a more rigorous threshold; it will only assume the value of 1 when HPR is above 0.6 basis points.

Although different HPR thresholds are used to create the training labels of both models, ultimately, the objective of the strategies is to yield a positive HPR for the investor. Therefore, although the Rigorous Logistic Regression model is trained to predict when HPR is above 0.6 basis points, it will be compared to a label that is 1 when HPR is above 0% and 0 otherwise.

Consequently, all confusion matrices and performance metrics presented are comparing the prediction of the model against a label that assumes the value of 1 when a positive HPR is observed and 0 otherwise. Therefore, the performance metrics are always going to be evaluating model performance for positive HPR prediction (before TC).

3.2.2 Strategy Performance Metrics

To evaluate Strategy Performance the following metrics are going to be defined:

$$Average\ Annualized\ HPR = \frac{\sum_{t=1}^{n} HPR_t}{n} \times (1440 \times 252) \quad (6)$$

The forex market is open, on average, 252 days per year, 24 hours per day. To estimate average annualized HPR, the average minute HPR was computed and multiplied by 1440 (number of minutes in 24 hours) and by 252.

$$Annualized\ Volatility = \sqrt{\frac{\sum_{t=1}^{n}(HPR_t - \overline{HPR})^2}{n} \times 1440 \times 252} \tag{7}$$

The annualized volatility was defined as the standard deviation of HPR. Since this dissertation works with a large dataset, no degree of freedom correction was needed.

$$Sharpe\ Ratio = \frac{Average\ Annualized\ HPR}{Annualized\ Volatility} \tag{8}$$

The Sharpe Ratio formula used in this dissertation is simplistic in the sense that omits the Risk-Free rate both in the numerator and denominator.[13]

This metric is one of the most widely used methods when obtaining a sense of risk-adjusted return. It compares the return of the strategy with the volatility. An investor is typically presented with a tradeoff between expected excess return and expected volatility. A risk-averse investor will only be willing to face more volatility if it expects higher return.

$$Cumulative\ HPR = \prod_{t=1}^{n}(1 + HPR_t) - 1 \tag{9}$$

A transformation that attempts to combine all minute HPR into a total HPR for the entire period.

$$Evolution\ of\ Wealth = \prod_{t=1}^{n}(1 + HPR_t) \tag{10}$$

The Evolution of Wealth has a very straightforward interpretation: A monetary unit invested at the beginning of the analysis period materialized into "*Evolution of Wealth*" monetary units at the end of the analysis period.

Evolution of Wealth = $Cumulative\ HPR + 1$

The process used to estimate Transaction Costs will be explained in Section 3.4.

[13] The Sharpe Ratio is usually defined as average excess returns divided by the volatility of excess returns.

To obtain the previously defined metrics including Transaction Costs, the HPR will be substituted by $Strategy\ HPR\ with\ TC$ (defined in Section 3.4).

3.3 Model Framework

All models are going to be applied in a rolling window.

The logistic regression algorithm is trained with a training set and then used to make predictions in a completely different test set. The purpose of this is to make OOS tests.

The model will predict 1 when it "believes" a HPR above a certain threshold is going to be met. For the Regular Logistic Regression model, this threshold will be an HPR above 0%. For the Rigorous Logistic Regression model, this threshold will be an HPR above 0.6 basis points.

It is important to reemphasize that the following chosen parameters and process might not be optimal. The purpose of this dissertation is not to have the best model and the best strategy. Instead, the objective of this study is to find out if with a simplistic but innovative machine learning approach, it is possible to obtain HPR predictability and construct a profitable trading strategy. Due to this reason and huge computational power requirements, these models' parameters were not tuned using a validation set. Instead, these variables were adjusted based on intuition for the EUR/USD model. After tuning for EUR/USD, a model with the same exact parameters was trained to other currencies and similar success was observed.

All models will be trained and tested in a rolling window with the following procedure:

i_k is an integer at iteration k and will take values from 1 to $\left\lfloor\frac{n-(1440\times3)}{60}\right\rfloor \times 60$, being $\lfloor\frac{a}{b}\rfloor$ the integer division of a by b, $\lfloor x \rfloor$ is the floor function of x, and n is the number of observations in the dataset.

If k is divisible by 24, the feature selection model explained in the following section is run.

For all iterations, training occurs in periods i_k to period $[\ i_k + (1440\ \times\ 3) - 1]$.

Each day has 1440 minutes, therefore the training period is 3 days or $(1440\ \times\ 3) = 4320$ periods.

After training, the model creates the prediction for the following 60 periods (1 hour), or periods $[\, i_k + (1440 \times 3)\,]$ to $[i_k + (1440 \times 3) + 60 - 1\,]$.

The value of i is updated by adding 60.

$$i_{k+1} = i_k + 60$$

This entire process is then repeated until predictions are made for the entire sample (except the first training period, corresponding to observations 1 to 4320).

To mitigate a possible loss of predictability caused by training the model in a training set that has a completely different behavioral nature than the test set, it is convenient to keep the training window sufficiently small in terms of time (3 days), but sufficiently large in terms of periods (4320 observations). This is one of the reasons the procedure taken is not easily applicable to other timeframes. Using the same method in an hourly timeframe, the model would be training in 72 observations and testing in the following period. This would highly increase the probability of not finding sufficient technical pattern observations during the 72-period training set and cause the model to make unsubstantiated decisions.

A shorter timeframe, such as second-data, would cause problems in profitability. Due to unchanging transaction costs, combined with inferior HPR (since there is typically lower volatility for lower timeframes), the investor would regularly fail to observe sufficient gain from implementing a long position.

It is also important to use a relatively larger window for training than the one used for prediction.

3.3.1 Feature Selection Model

The relevance of each explanatory variable for HPR predictability might change dramatically over time.

Due to possible multicollinearity problems, inclusion of many redundant variables and lack of computing power, both models that this dissertation proposes will only use a limited number of

5 explanatory variables for each 24 iterations. As mentioned previously, in each iteration k, a prediction is made for the following 60 minutes, therefore the feature selection will be updated every 24 hours.

An experimental model using 10 chosen inputs every 24 iterations was also tested and obtained a poorer performance, caused by irrelevant variable inclusion and possible multicollinearity problems.

This chapter will explain how these 5 best explanatory variables are selected to use for prediction in the next 24 hours.

Each 24 iterations, the feature selection model is run before doing the predictions for the following 60 periods.

This model is trained in the usual training set (defined in the previous chapter), but uses all 100 explanatory variables.

The absolute value of the regression coefficients associated with these 100 explanatory variables is retrieved and sorted.

The new explanatory variables to use for the present iteration and the next 23 are going to be the ones that had the top 5 highest absolute value of the regression coefficients.

This process ignores the p-values of the explanatory variables hence, admittedly, might not be optimal. However, it has the advantage of simplicity and is a common practice when analyzing feature importance (e.g., Agirrezabal & Amann, 2022).

3.4 Transaction Costs implementation

A profitable trading strategy must perform sufficiently well to cover TC. These are especially relevant when trading at higher frequencies (such as minute data), particularly due to the Bid-Ask spread.

Some price volatility is necessary to observe positive HPR. The higher the volatility, the greater is the probability of observing HPR above a certain threshold (*caeteris paribus*).

When an investor is trading at shorter time-horizons, the lower price volatility might be insufficient to produce an HPR that surpasses the Bid-Ask spread.

In this study, TC are considerably simplified and are estimated through the proportional Bid-Ask spread of the close price.

$$Proportional\ Bid\ Ask\ Spread_t = \frac{Ask\ Close\ Price_t - Bid\ Close\ Price_t}{Ask\ Close\ Price_t} \tag{11}$$

Whenever the agent sells its position (when the weight changes from 1 to 0), the proportional Bid-Ask spread for that time-period will indicate what is the percentage of wealth destroyed due to the transaction.[14]

The strategy HPR in period t with included transaction costs will therefore be defined as:

$$Strategy\ HPR\ with\ TC_t = (1 + Strategy\ HPR_t) \times (1 - Proportional\ Bid\ Ask\ Spread_t) - 1 \tag{12}$$

Where,

$$Strategy\ HPR_t = Weight_t \times Currency\ HPR_t \tag{13}$$

4 Models and Results

For the sake of simplicity, two different models are going to be named in an informal manner that transcribes well their behavior. The first model is going to be named the "Regular Logistic Regression" and the second model is the "Rigorous Logistic Regression". Both models are described, applied, and the results are analyzed in the following sections.

[14] Giving a practical example: If an investor has a total wealth of €100 and buys a security for this value (the Ask price is equal to €100) but can only sell at €95 (Bid price), the proportional Bid-Ask spread will be 5%. This means that if the investor decides to sell the security immediately, his/her wealth will decrease by 5%.

4.1 Regular Logistic Regression model

The label used to train the regular logistic regression model takes the value of 1 when the HPR of the underlying currency exchange rate is positive and 0 otherwise. The probability threshold is set to 50%.

Using the process previously defined in the Model Framework and Feature Selection Model sections, the following results were obtained.

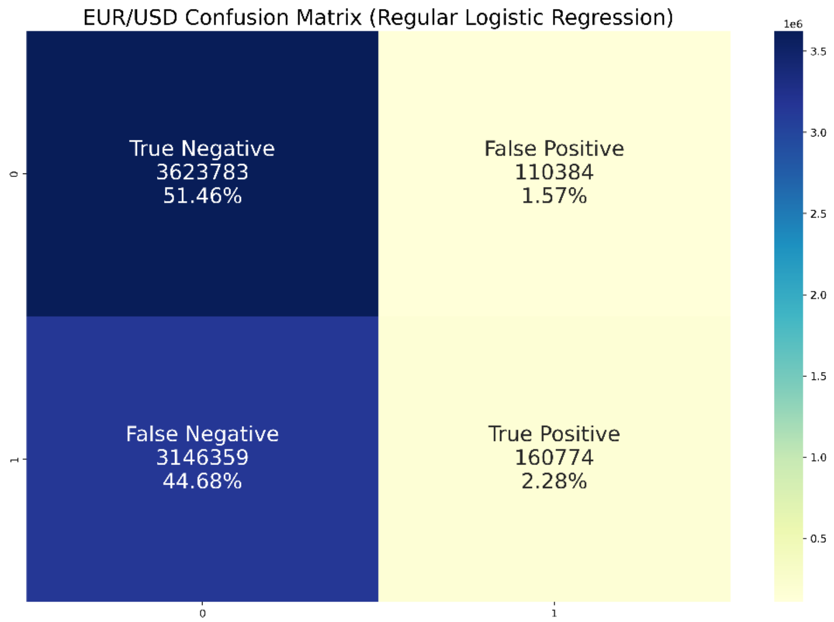
4.1.1 EUR/USD

The Regular Logistic Regression model, applied to the EUR/USD currency exchange rate, predicted a positive HPR 3.85% of the times. The percentage of observed positive HPR for the EUR/USD currency exchange rate, during the full sample prediction was 46.968% (Table 1 in page 6 presents different values because it does not show the full period of prediction).

Since the percentage of observed positive HPR is relatively close to 50%, there is no need to consider data imbalance problems when reviewing the following performance metrics.

The following Confusion Matrix (Figure 11) is relative to the EUR/USD currency exchange rate, comparing the full set of predictions against a label that takes the value of 1 when the HPR_t of EUR/USD is positive and 0 otherwise. The prediction window is from 2003-05-07 21:03:00 until 2022-03-04 21:30:00.

Figure 11



$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \approx 0.5929$$

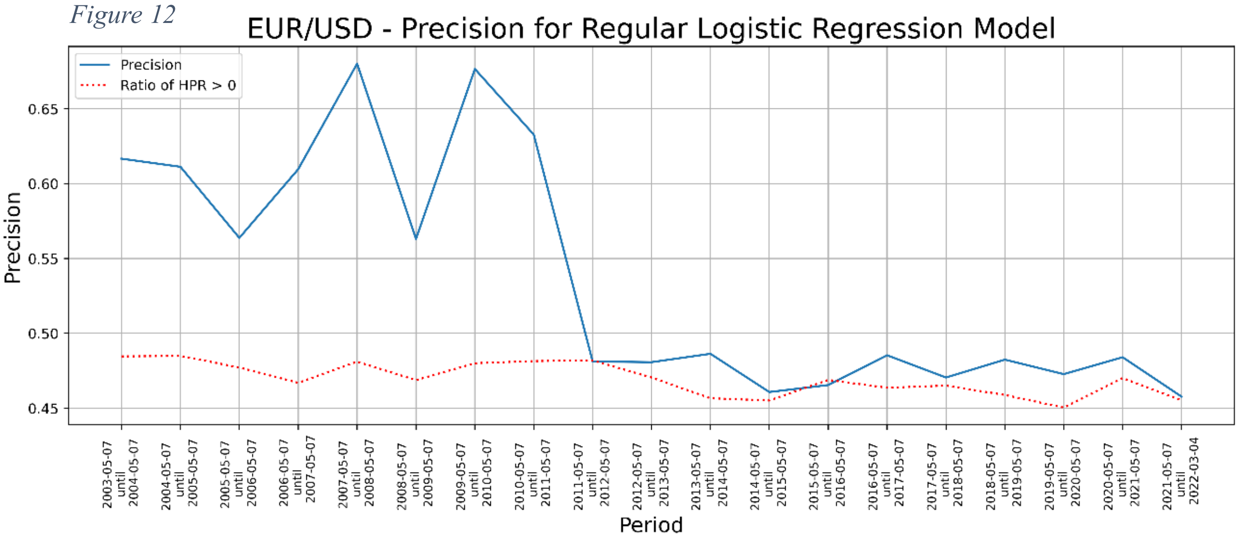
During the entire prediction set, when the model predicted a positive HPR, the probability of having observed one was 59.29%.

If the investor had taken a long position when the model predicted, he/she would've observed a positive HPR before transaction costs 59.29% of the time. If the agent would've chosen to simply hold the currency pair throughout the full sample, 46.968% of the periods he/she would have observed a positive HPR before transaction costs.

This by itself is evidence of some predictability caused by using only TA indicators as regressors.

Figure 12 shows the evolution of precision at a yearly timeframe.

Figure 12



The red dotted line is the ratio of positive HPR observed in the respective period.

As it is apparent, precision declined substantially, but managed to remain above the ratio of positive HPR, being this an indication of consistent predictability throughout the full prediction period.

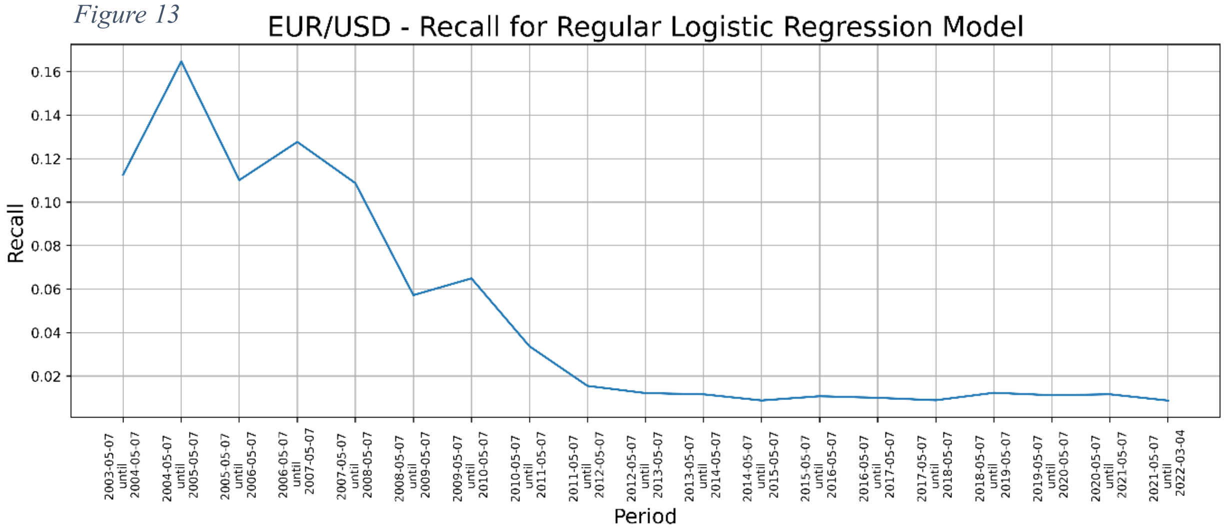
$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} \approx 0.0486$$

Recall can be interpreted as, amongst all positive HPR observed in the underlying currency exchange rate, what was the ratio of these detected by the model.

The model was only capable of detecting 4.86% of the observed positive HPR.

Figure 13 presents the evolution of Recall.

Figure 13



Recall decreased substantially and plateaued around 2012.

A decreasing Recall can be the result of declining True Positives or increasing False Negatives. Figures 14 and 15 show the evolution of both:

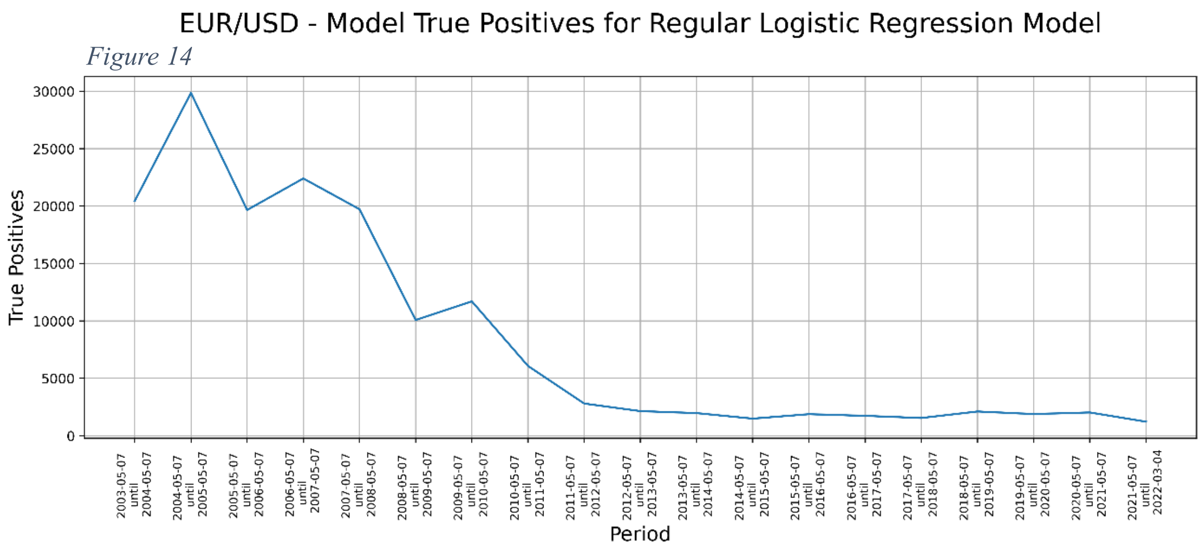


Figure 14

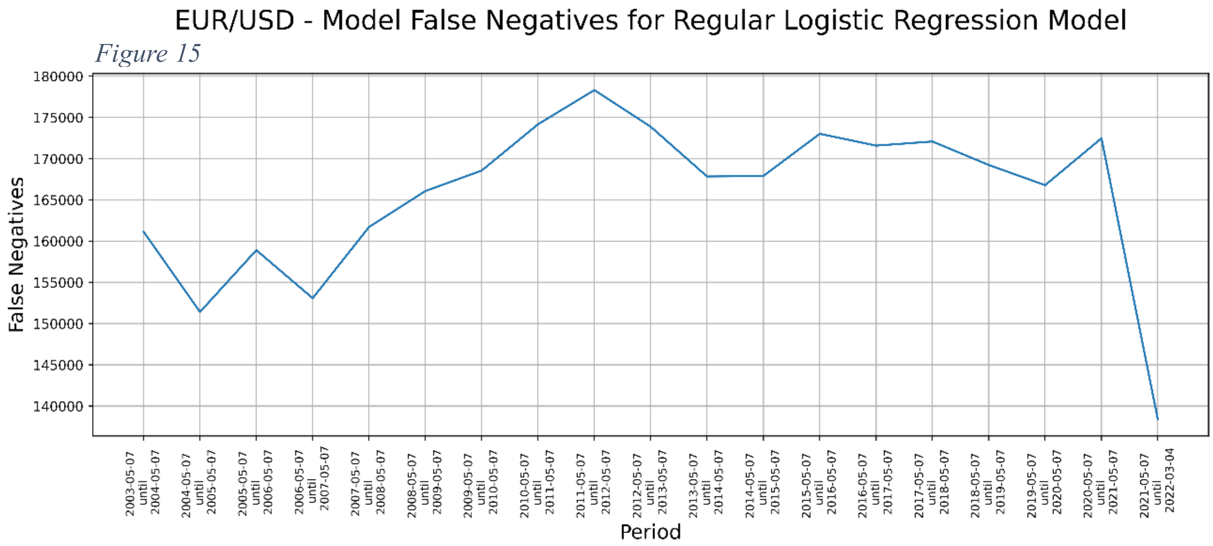


Figure 15

It is important to notice that the last period is shorter, explaining the sudden drop in False Negatives (Figure 15).

From the previous figures it is possible to discern that the main cause of recall decrease was the substantial decline of True Positives (Figure 14). The model did not predict as many positive HPR for later periods, although the ratio of positive HPR observed remained similar (presented as the red dotted line in page 27, Figure 12).

For the regular logistic regression model, if the probability threshold is above 50%, the model is confident enough to implement a "buy" position. If the model is training against a label that has a smaller percentage of positive HPR observations (46.968 %) and is unable to find a linear relationship between the given inputs and positive HPR, the optimal probability for the model to output is 46.968%, repeatedly predicting a negative HPR. Therefore, the sharply declining recall presented in Figure 13 might be explained by a loss of regressors' capacity of linearly explaining HPR.

This can also be further observed in Figure 16 which shows the percentage of positive classifications done by the model across time.

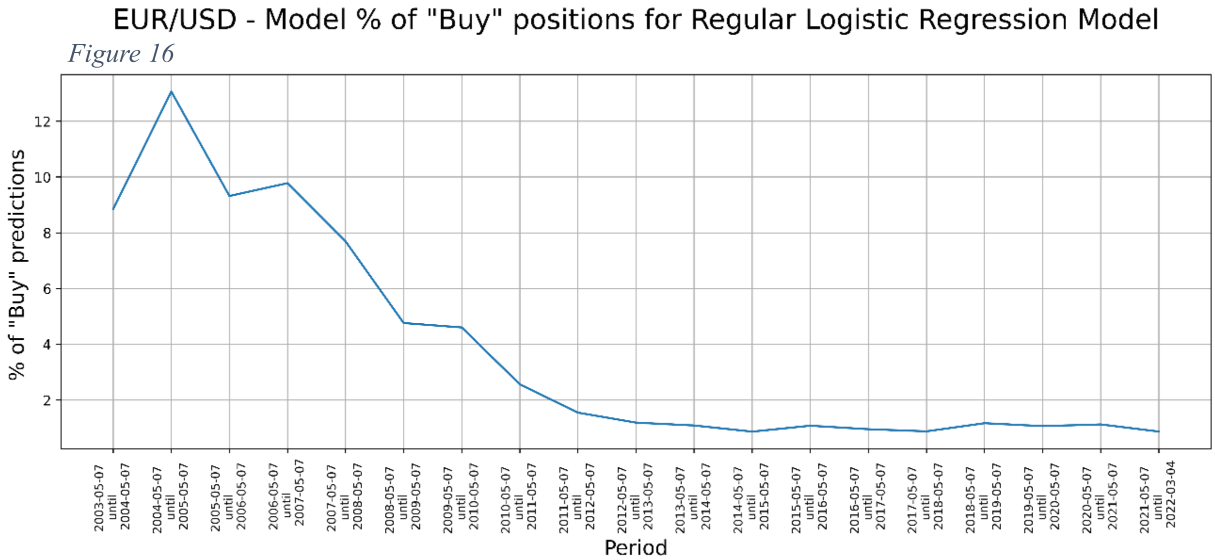


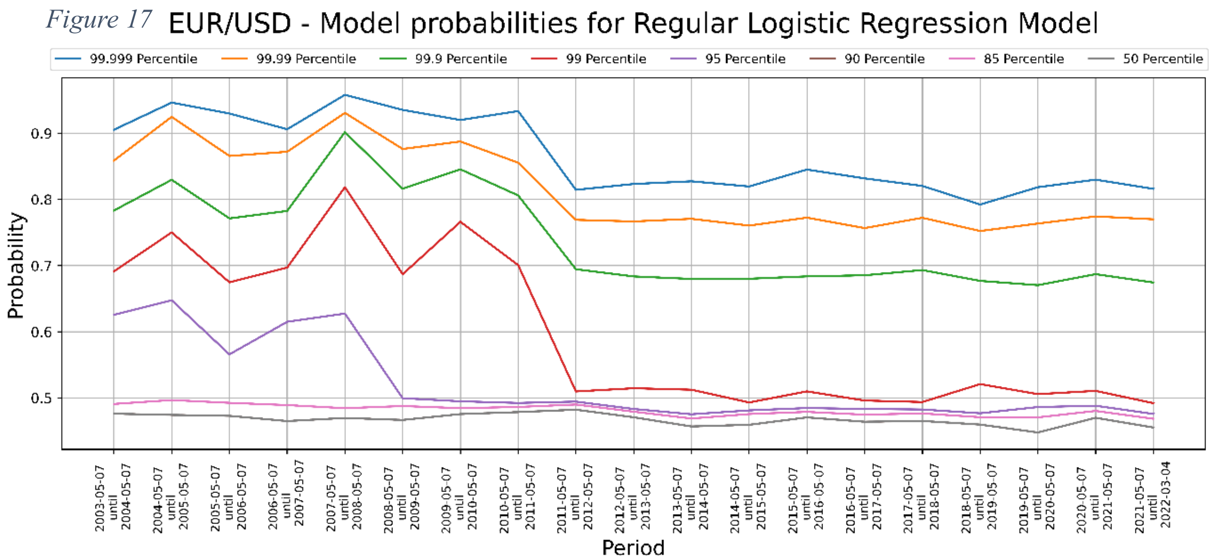
Figure 16

Notice how remarkably similar Figure 16 is in relation to Figure 14 and Figure 13.

The decreasing certainty of the model can also be observed when analyzing the evolution of the top percentiles for the logistic regression's probability outputs.

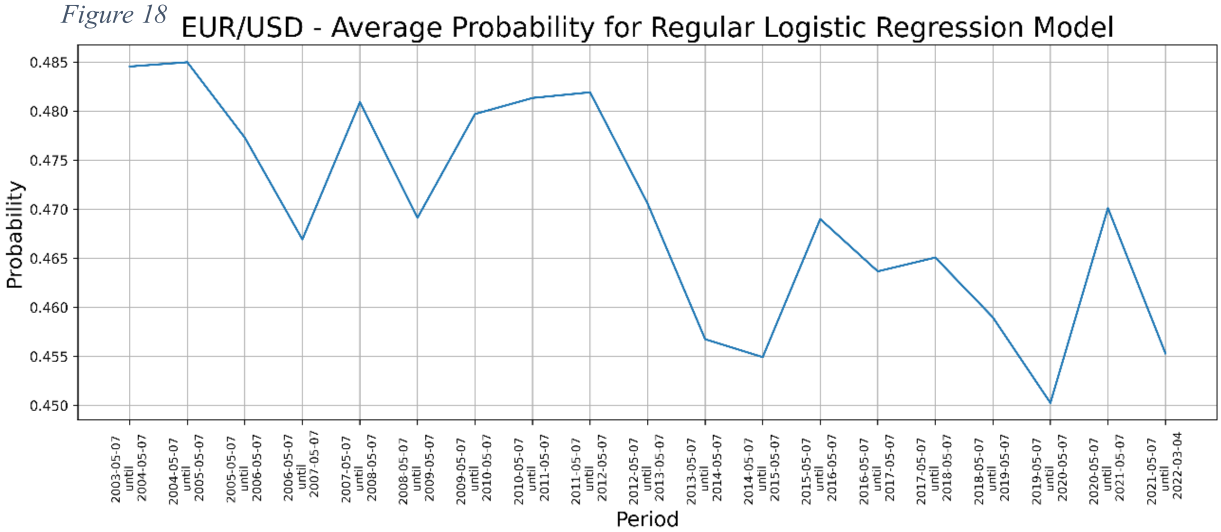
In the following chart (Figure 17) the top percentiles of the logistic regression probability outputs are presented, being evident a significant decrease, especially for the 99 percentile, from 2011/05/07 onwards.

Figure 17



Although these results were observed, average probability didn't change substantially during the full sample of data (Figure 18).

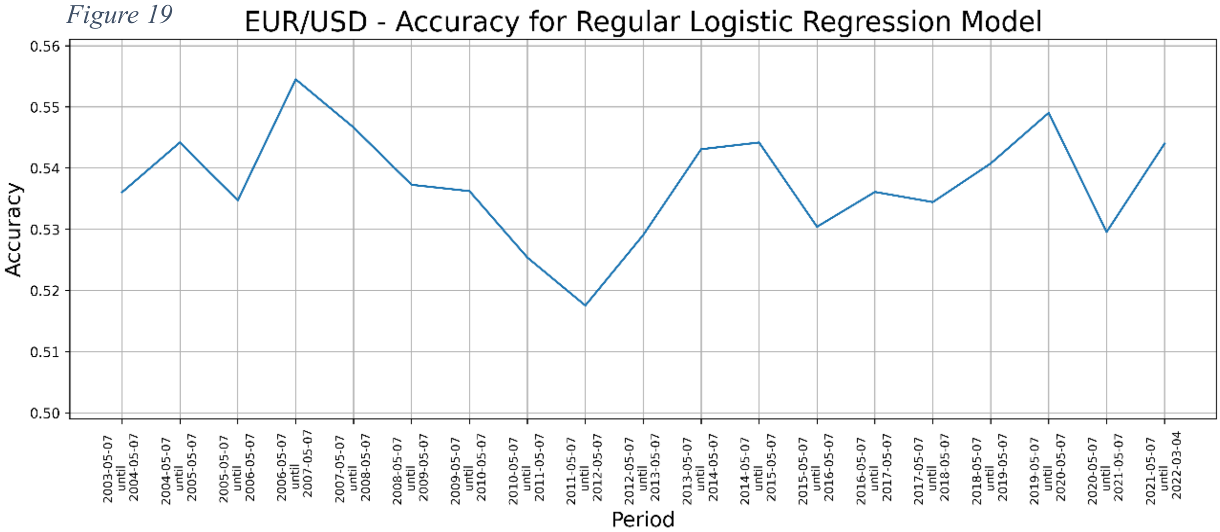
Figure 18



$$Accuracy = \frac{True\ Positives + True\ Negatives}{True\ Positives + False\ Negatives + True\ Negatives + False\ Positives} \approx 0.5375$$

Accuracy is the fraction of predictions the model was correct. In Figure 19, it is possible to observe that this measure didn't change substantially over time and that it maintained above 50% throughout the whole prediction set.

Figure 19



4.1.1.1 Investment Strategy Performance Before Transaction Costs

From the Strategy HPR vector (also defined in Section 3.4, equation 13),

$$Strategy\ HPR_t = Weight_t \times Currency\ HPR_t \tag{13}$$

several strategy performance indicators, previously defined in Section 3.2.2, are computed and compared against the contemporaneous results for the EUR/USD currency exchange rate.

Table 2 presents this comparison over the full prediction period.

Table 2

Regular Logistic Regression Strategy Performance Before Transaction Costs		
Performance Metric	**Strategy EUR/USD**	**EUR/USD currency exchange rate**
Average Annualized HPR	51.7664%	0.2959%
Annualized Volatility	2.2365%	9.9700%
Sharpe Ratio	23.1462	0.0297
Cumulative Return	2292119.9490%	-3.8272%
Evolution of Wealth	22922.1995	0.9617

The performance of the strategy before transaction costs looks very promising, but it is far from realistic. As mentioned in the Transaction Costs implementation section, these strategies are highly sensitive to the implementation of TC. This is because these astonishing returns are coming from a huge number of very small, almost negligible positive returns. As we shall see when implementing TC, these small HPR, on average, do not surpass the proportional Bid-Ask spread and will destroy wealth for the investor.

Table 3 and Table 4 present the evolution of the performance metrics exhibited in Table 2.

Table 3

Regular Logistic Regression Strategy Performance Before Transaction Costs (EUR/USD)				
Period	**Annualized HPR (%)**	**Annualized Volatility (%)**	**Sharpe Ratio**	**Cumulative Return (%)**
2003-05-07 21:03:00 - 2004-05-07 21:03:00	153.681	3.922	39.187	388.452
2004-05-07 21:03:00 - 2005-05-07 21:03:00	219.835	4.167	52.758	862.011
2005-05-07 21:03:00 - 2006-05-07 21:03:00	100.692	3.508	28.706	182.285
2006-05-07 21:03:00 - 2007-05-07 21:03:00	121.664	3.054	39.844	252.379
2007-05-07 21:03:00 - 2008-05-07 21:03:00	164.902	2.731	60.381	454.833
2008-05-07 21:03:00 - 2009-05-07 21:03:00	40.450	3.185	12.698	51.947
2009-05-07 21:03:00 - 2010-05-07 21:03:00	114.404	2.679	42.697	226.569
2010-05-07 21:03:00 - 2011-05-07 21:03:00	54.473	2.199	24.767	75.375
2011-05-07 21:03:00 - 2012-05-07 21:03:00	-2.481	1.377	-1.802	-2.546
2012-05-07 21:03:00 - 2013-05-07 21:03:00	-0.237	0.958	-0.247	-0.249
2013-05-07 21:03:00 - 2014-05-07 21:03:00	0.963	0.754	1.278	0.989
2014-05-07 21:03:00 - 2015-05-07 21:03:00	0.554	0.876	0.632	0.565
2015-05-07 21:03:00 - 2016-05-07 21:03:00	-1.223	1.508	-0.811	-1.261
2016-05-07 21:03:00 - 2017-05-07 21:03:00	0.551	0.933	0.590	0.564
2017-05-07 21:03:00 - 2018-05-07 21:03:00	0.396	0.689	0.575	0.406
2018-05-07 21:03:00 - 2019-05-07 21:03:00	0.850	0.751	1.132	0.875
2019-05-07 21:03:00 - 2020-05-07 21:03:00	1.569	0.701	2.237	1.630
2020-05-07 21:03:00 - 2021-05-07 21:03:00	1.109	0.763	1.453	1.138
2021-05-07 21:03:00 - 2022-03-04 21:30:00	-0.568	0.613	-0.927	-0.480

Table 4

EUR/USD Exchange Rate				
Period	**Annualized HPR (%)**	**Annualized Volatility (%)**	**Sharpe Ratio**	**Cumulative Return (%)**
2003-05-07 21:03:00 - 2004-05-07 21:03:00	5.151	12.921	0.399	4.558
2004-05-07 21:03:00 - 2005-05-07 21:03:00	7.942	10.665	0.745	7.891
2005-05-07 21:03:00 - 2006-05-07 21:03:00	-0.137	10.083	-0.014	-0.663
2006-05-07 21:03:00 - 2007-05-07 21:03:00	6.763	8.568	0.789	6.849
2007-05-07 21:03:00 - 2008-05-07 21:03:00	12.284	8.947	1.373	13.147
2008-05-07 21:03:00 - 2009-05-07 21:03:00	-12.085	16.275	-0.743	-12.965
2009-05-07 21:03:00 - 2010-05-07 21:03:00	-4.135	11.120	-0.372	-4.799
2010-05-07 21:03:00 - 2011-05-07 21:03:00	11.953	11.970	0.999	12.291
2011-05-07 21:03:00 - 2012-05-07 21:03:00	-8.264	11.438	-0.723	-8.823
2012-05-07 21:03:00 - 2013-05-07 21:03:00	0.563	8.538	0.066	0.205
2013-05-07 21:03:00 - 2014-05-07 21:03:00	6.270	7.116	0.881	6.359
2014-05-07 21:03:00 - 2015-05-07 21:03:00	-20.014	9.634	-2.078	-18.944
2015-05-07 21:03:00 - 2016-05-07 21:03:00	1.793	11.369	0.158	1.186
2016-05-07 21:03:00 - 2017-05-07 21:03:00	-2.966	9.094	-0.326	-3.421
2017-05-07 21:03:00 - 2018-05-07 21:03:00	7.954	7.462	1.066	8.216
2018-05-07 21:03:00 - 2019-05-07 21:03:00	-5.917	7.036	-0.841	-6.147
2019-05-07 21:03:00 - 2020-05-07 21:03:00	-2.881	7.390	-0.390	-3.202
2020-05-07 21:03:00 - 2021-05-07 21:03:00	11.612	7.051	1.647	12.327
2021-05-07 21:03:00 - 2022-03-04 21:30:00	-12.531	6.325	-1.981	-10.199

Table 3 shows that the strategy's outstanding performance was due to the first 8 years. After this period, the observed Annualized HPR declined substantially to almost negligible values.

Even so, the Regular Logistic regression seemed to produce much better results than holding the EUR/USD currency pair, both in terms of HPR but also volatility and, therefore, Sharpe Ratio. Since the model only predicts a positive HPR 3.85% of the times, this causes an extremely low volatility, especially for later periods when the model is less certain and has a smaller recall.

4.1.1.2 Investment Strategy Performance After Transaction Costs

The same performance metrics are computed as before, but this time applying TC with the process explained in Section 3.4.

Table 5

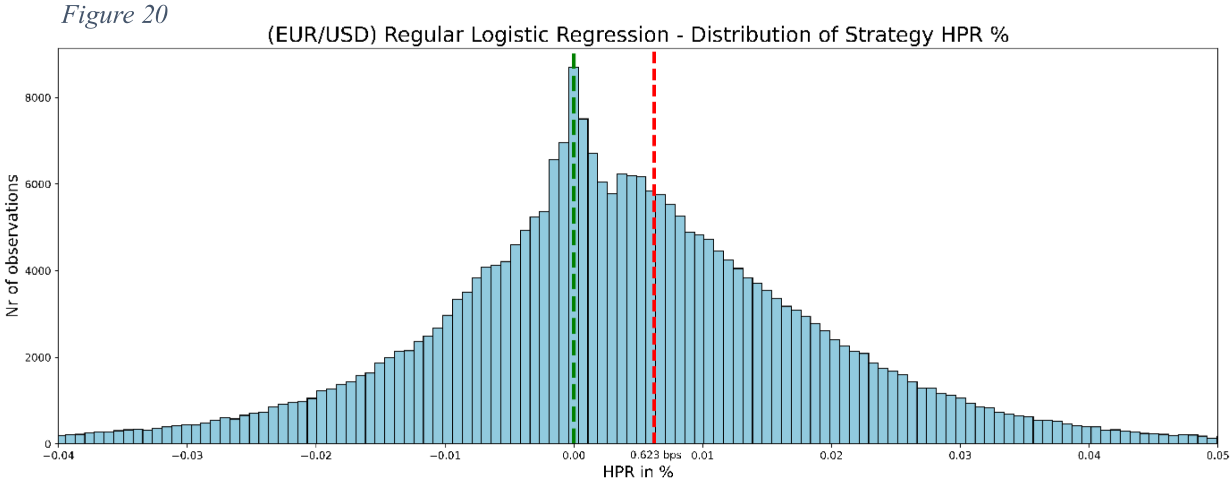
Regular Logistic Regression Strategy Performance After Transaction Costs		
Performance Metric	**Strategy EUR/USD**	**EUR/USD currency exchage rate**
Average Annualized HPR	-47.6413%	0.2959%
Annualized Volatility	2.1939%	9.9700%
Sharpe Ratio	-21.7153	0.0297
Cumulative Return	-99.9904%	-3.8272%
Evolution of Wealth	0.000096	0.9617

From the Evolution of Wealth results in Table 5, investing 1 monetary unit and using this strategy throughout the full prediction period, would decrease the wealth to 0.000096 monetary units.

The outstanding performance of the strategy completely disappeared after Transaction Costs.

The reason was previously explained in the Transaction Costs implementation section: Since this research is being implemented in minute data, rarely a positive HPR is observed sufficiently high to cover the Bid-Ask spread (Figure 20).

Figure 20



In Figure 20, the distribution of the strategy HPR is presented. The red dotted line corresponds to the average proportional bid-ask spread observed for the EUR/USD full prediction period. The green dotted line represents the value in which HPR = 0. As it is possible to discern, the majority of the HPR from the implemented strategy, although positive, does not cover the average proportional bid-ask spread. This is the cause of wealth destruction for the investor.

Ironically, when we account for TC, the models' high confidence during the first 8 years was detrimental to the investor. This is because the model will implement long positions regularly that, even though have a higher probability of being positive, do not cover the proportional Bid-Ask Spread, causing the investor to lose wealth (Figure 20).

Table 6 presents the evolution of the metrics presented in table 5.

Table 6

Regular Logistic Regression Strategy Performance After Transaction Costs (EUR/USD)				
Period	**Annualized HPR (%)**	**Annualized Volatility (%)**	**Sharpe Ratio**	**Evolution of Wealth**
2003-05-07 21:03:00 - 2004-05-07 21:03:00	-139.044	3.804	-36.550	0.238
2004-05-07 21:03:00 - 2005-05-07 21:03:00	-138.714	3.946	-35.154	0.239
2005-05-07 21:03:00 - 2006-05-07 21:03:00	-146.965	3.482	-42.211	0.220
2006-05-07 21:03:00 - 2007-05-07 21:03:00	-179.673	3.073	-58.460	0.155
2007-05-07 21:03:00 - 2008-05-07 21:03:00	-82.528	2.554	-32.312	0.424
2008-05-07 21:03:00 - 2009-05-07 21:03:00	-52.568	3.279	-16.034	0.580
2009-05-07 21:03:00 - 2010-05-07 21:03:00	7.822	2.497	3.133	1.084
2010-05-07 21:03:00 - 2011-05-07 21:03:00	-14.668	2.104	-6.971	0.859
2011-05-07 21:03:00 - 2012-05-07 21:03:00	-29.707	1.453	-20.448	0.735
2012-05-07 21:03:00 - 2013-05-07 21:03:00	-25.186	1.035	-24.325	0.771
2013-05-07 21:03:00 - 2014-05-07 21:03:00	-7.544	0.767	-9.833	0.926
2014-05-07 21:03:00 - 2015-05-07 21:03:00	-7.027	0.886	-7.928	0.930
2015-05-07 21:03:00 - 2016-05-07 21:03:00	-13.592	1.552	-8.759	0.869
2016-05-07 21:03:00 - 2017-05-07 21:03:00	-10.575	0.976	-10.840	0.897
2017-05-07 21:03:00 - 2018-05-07 21:03:00	-8.748	0.710	-12.325	0.914
2018-05-07 21:03:00 - 2019-05-07 21:03:00	-13.286	0.817	-16.267	0.872
2019-05-07 21:03:00 - 2020-05-07 21:03:00	-12.195	0.749	-16.272	0.882
2020-05-07 21:03:00 - 2021-05-07 21:03:00	-11.758	0.815	-14.434	0.887
2021-05-07 21:03:00 - 2022-03-04 21:30:00	-10.936	0.691	-15.837	0.912

Using this strategy, the investor consistently destroys wealth each period, being the period between 2009-05-07 until 2010-05-07 the only observed where the HPR was positive.

Although this model showed signs of predictability and presented fantastic results before accounting for transaction costs, it completely failed to deliver them after TC.

This same procedure was applied to the USD/JPY and GBP/CHF currency pairs and similar results were observed. All models show some predictability before transaction costs, but the returns completely fade once they are included.

These results inspired the creation of a more "rigorous" logistic regression model.

4.2 Rigorous Logistic Regression model

As previously mentioned, the Regular Logistic Regression model presented promising predictability but performed poorly after accounting for transaction costs.

Even though the model shows some HPR predictability, it is not sufficiently high to consistently surpass the proportional Bid-Ask spread and therefore destroys investors' wealth.

To detour this problem, a logistic regression model with threshold-moving and a different training label was implemented.

The following logistic regression model was tweaked to increase precision and predict a positive HPR only if the model is considerably certain. This is useful because TC exist, and the investor should have sufficient confidence it will observe HPR above a certain threshold to feel comfortable in taking a long position.

The label used to train this model takes the value of 1 when the HPR of the underlying currency exchange rate is above 0.6 bps and 0 otherwise. This means that the model will only implement a long position when it "believes" HPR will be above 0.6 bps. The probability threshold will also be shifted to 60%.

These procedures were applied in hopes that, when an investment prediction is made, the probability of observing a positive HPR after TC substantially increases. By setting the model to implement a long position when it predicts a HPR above 0.6 bps and has a confidence of at least 60%, the probability of observing a positive HPR before and after TC should be much higher.

It is expected for this procedure to impact the model performance metrics by increasing precision but decreasing recall.

As mentioned in previous chapters, precision is the ratio of correctly predicted events in all events predicted. Increasing the probability threshold and increasing the HPR threshold of the training label, should increase the models' precision when discerning between a positive HPR and a negative HPR.

This model is also expected to have an even lower recall. Since the threshold probability is higher, the model will implement less "buy" positions and the percentage of detected positive HPR amongst all positive HPR observed will be substantially lower. The fact that the model will be trained against a label that is 1 when HPR is above 0.6 bps should only increase precision and decrease recall even further.

This result is very well documented in machine learning as the Precision-Recall Trade-off.

Typically, it is beneficial for a model to have high precision and high recall. However, when measures are implemented to increase one, the other tends to decrease.

Many times, data scientists plot a Precision-Recall curve to summarize this trade-off. Since a high precision and a high recall is preferable, a typical model performance metric is calculating the Area Under the Curve (AUC) of this Precision-Recall curve.

Although it would be beneficial to predict more positive HPR than the ones the model is predicting, the real problem of the Regular Logistic regression model comes after transaction costs implementation, and the impact that a failed prediction has in the model. Therefore, the main worry when producing a wealth creating strategy is increasing the precision.

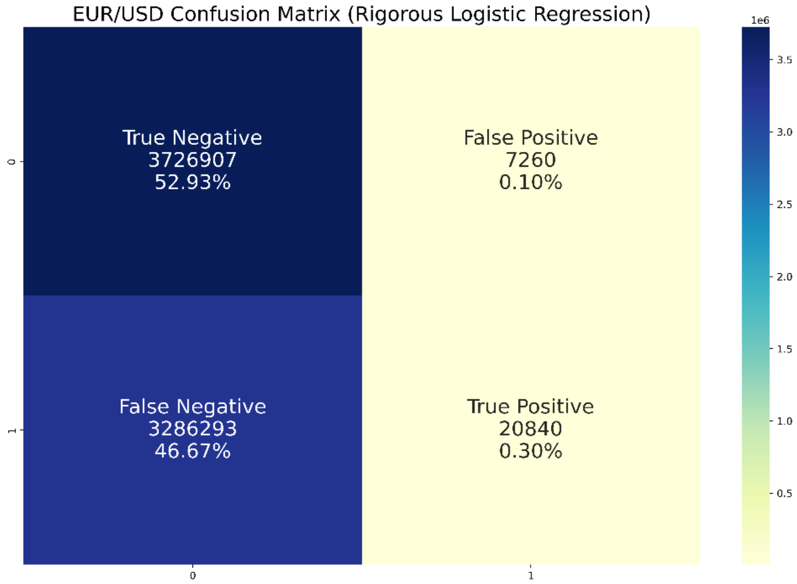
Recall is not nearly as relevant. A lower recall, everything else constant, also contributes to a decreased strategy volatility, having a positive impact in the Sharpe Ratio of the Strategy. This is the reason why the Precision-Recall curve is not analyzed, neither its AUC.

4.2.1 EUR/USD

The Rigorous Logistic Regression model, applied to the EUR/USD currency exchange rate, made a positive HPR prediction only 0.399% of the times (compared to 3.85% for the Regular Logistic Regression model).

The following Confusion Matrix (Figure 21) is relative to the EUR/USD currency exchange rate, comparing the full set of predictions against a label that takes the value of 1 when the HPR_t is positive and 0 otherwise. The prediction window is from 2003-05-07 21:03:00 until 2022-03-04 21:30:00.

Figure 21



$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \approx 0.7416$$

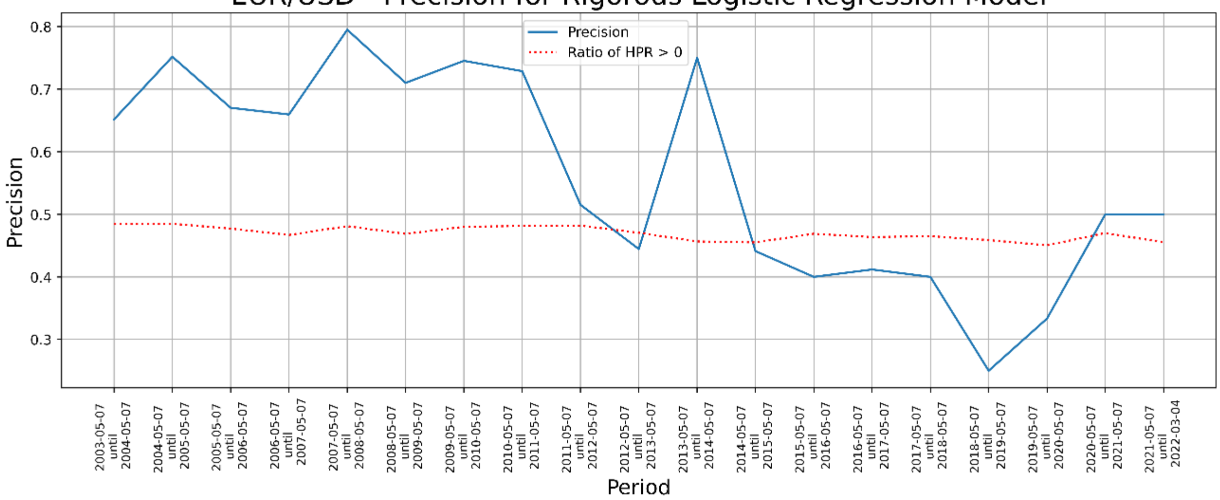
During the entire prediction set, when the model predicted a HPR above 0.6 bps, the probability of having observed one above 0% was 74.16%.

This is a substantial increase in precision comparing with the 59.29% of the Regular Logistic Regression model.

If the investor had taken a long position when the model predicted, he/she would've observed a positive HPR before transaction costs 74.16% of the time. If the agent would've chosen to simply hold the currency pair throughout the full prediction period, 46.968% of the times he/she would have observed a positive HPR.

Figure 22 shows the evolution of precision.

Figure 22



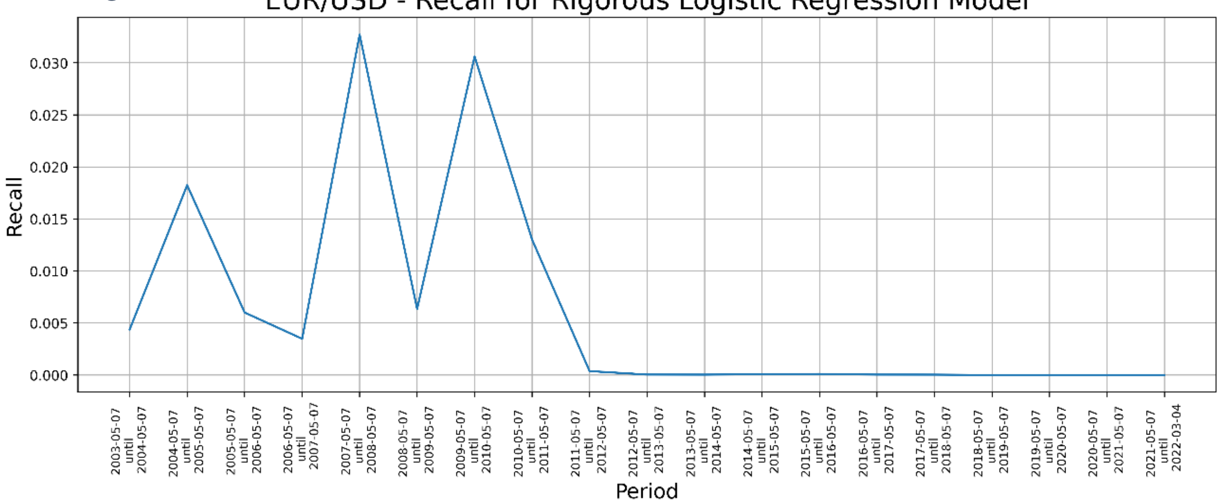
Similarly to the Regular Logistic Regression model, precision declined substantially. In this model however, it did not consistently surpass the ratio of positive HPR for the contemporaneous time-period. Showing evidence of lack of prediction capacity of positive HPR for later time periods.

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} \approx 0.0063$$

The model was only capable of detecting 0.63% of the observed positive HPR (comparing with 4.86% for the Regular Logistic Regression model).

Figure 23 presents the evolution of Recall

Figure 23



Recall was extremely volatile during the first decade of prediction but sharply fell to barely 0 during the second decade.

A decreasing Recall can be a result of declining True Positives or increasing False Negatives. The following figures show the evolution of both (Figure 24 and 25).

Figure 24

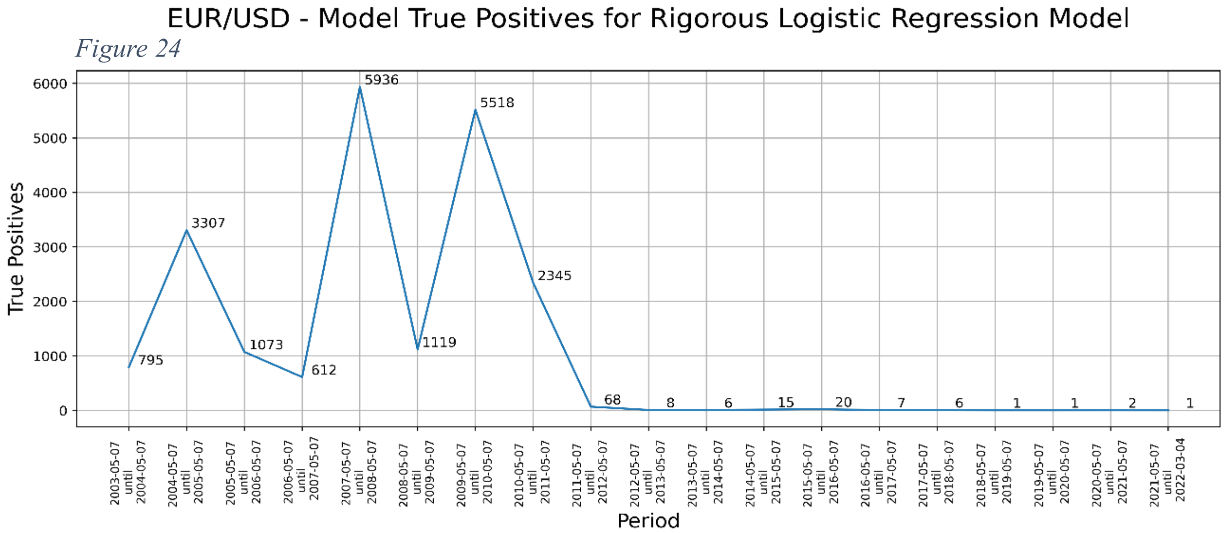
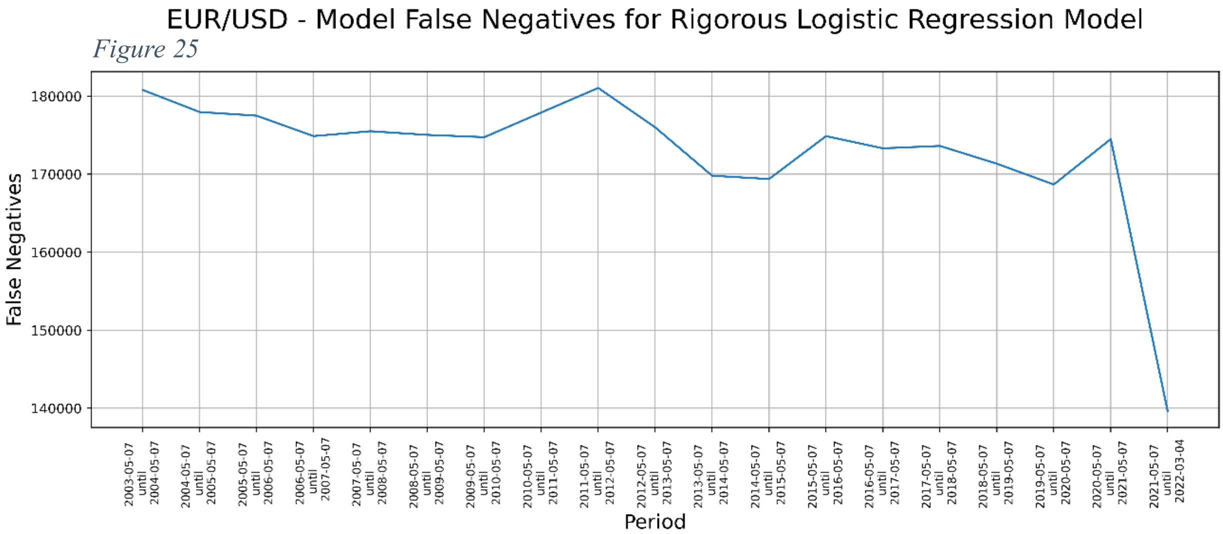


Figure 25



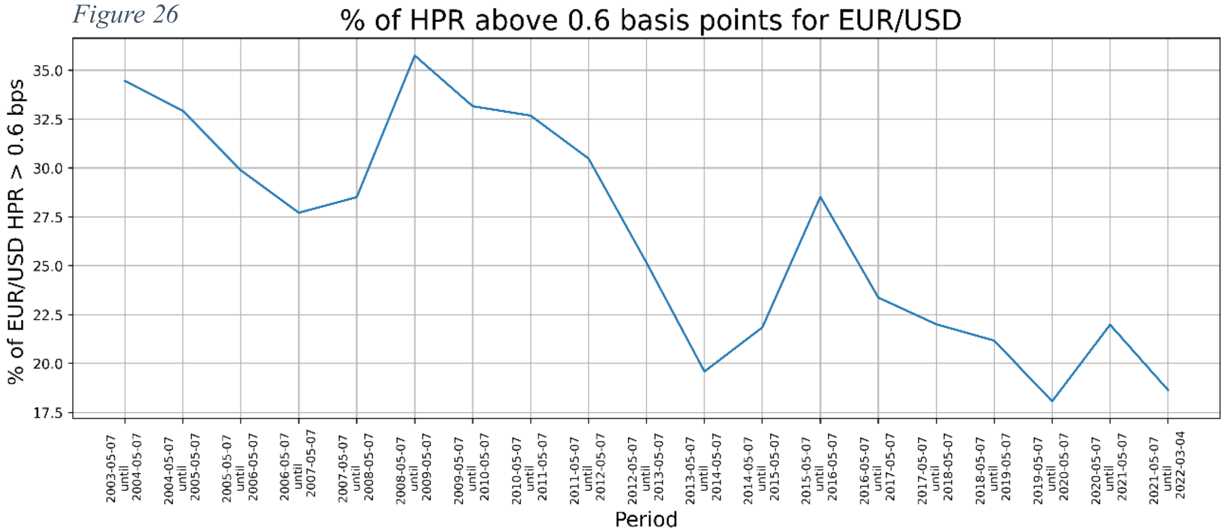
As before, the last period is shorter, explaining the sudden drop in False Negatives (Figure 25).

From the previous figures it is possible to discern that the main cause of recall decrease was the same as in the Regular Logistic Regression model.

The evolution of recall across time is remarkably similar to the evolution of True Positives. It is therefore possible to infer that the reason recall collapsed for the second decade of prediction was due to the substantial decline of True Positives.

The model did not predict as many HPR above 0.6 basis points for later periods. This, in part, can be explained by a decreasing number of observations of positive HPR above 0.6 basis points for the EUR/USD exchange pair (Figure 26).

Figure 26

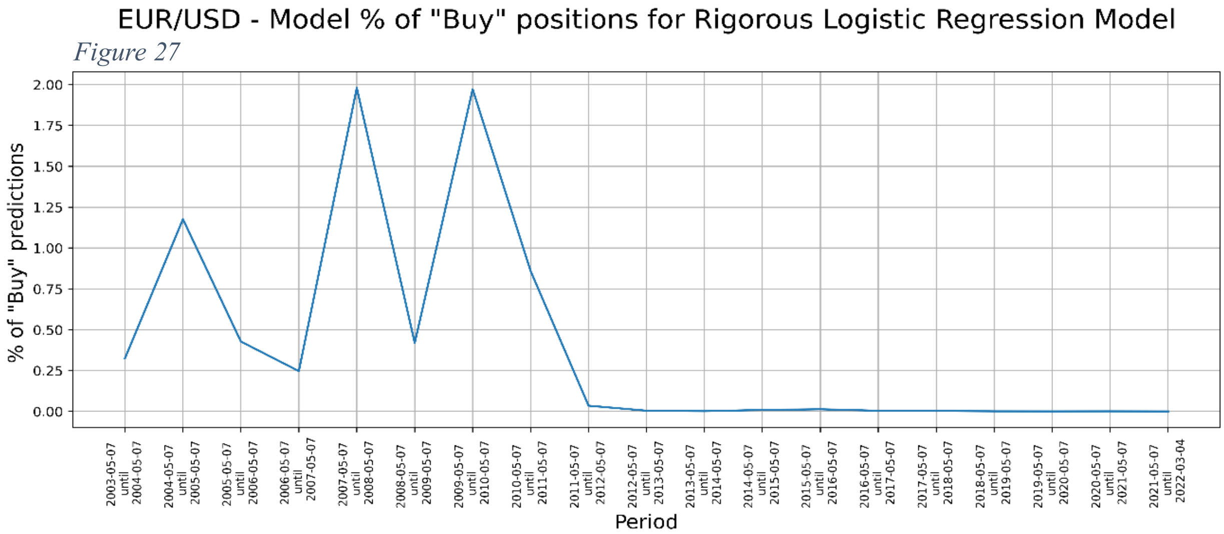


Although the percentage of EUR/USD HPR above 0.6 basis points decreased to half along the prediction period, this factor alone is not able to explain the severe decrease of True Positives.

As in the Regular Logistic Regression model, the explanation for the decrease in recall comes mainly from the loss of confidence when predicting.

The model cannot find a linear combination of the technical analysis inputs that explain HPR above 0.6 bps in a satisfactory manner, therefore it barely yields probabilities above 60% and does not implement a long position. This can also be observed in Figure 27 which presents the percentage of positive predictions done by the model across time.

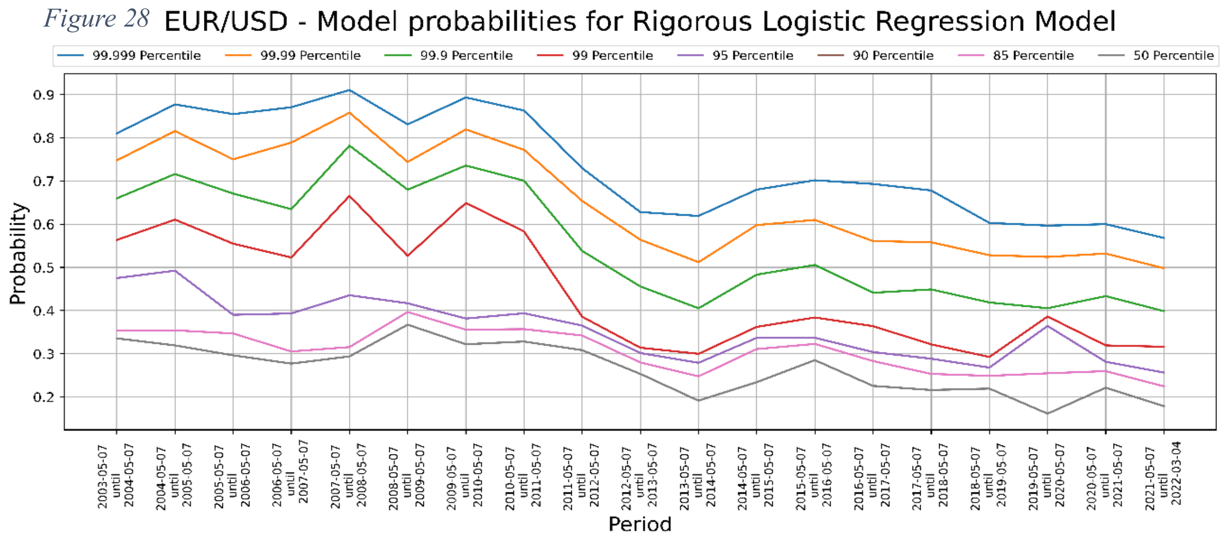
Figure 27



The previous chart (Figure 27) matches the evolution of recall (Figure 23) remarkably well.

The decreasing certainty of the model can once again be observed when analyzing the logistic regression's top percentiles probability output evolution (Figure 28).

Figure 28



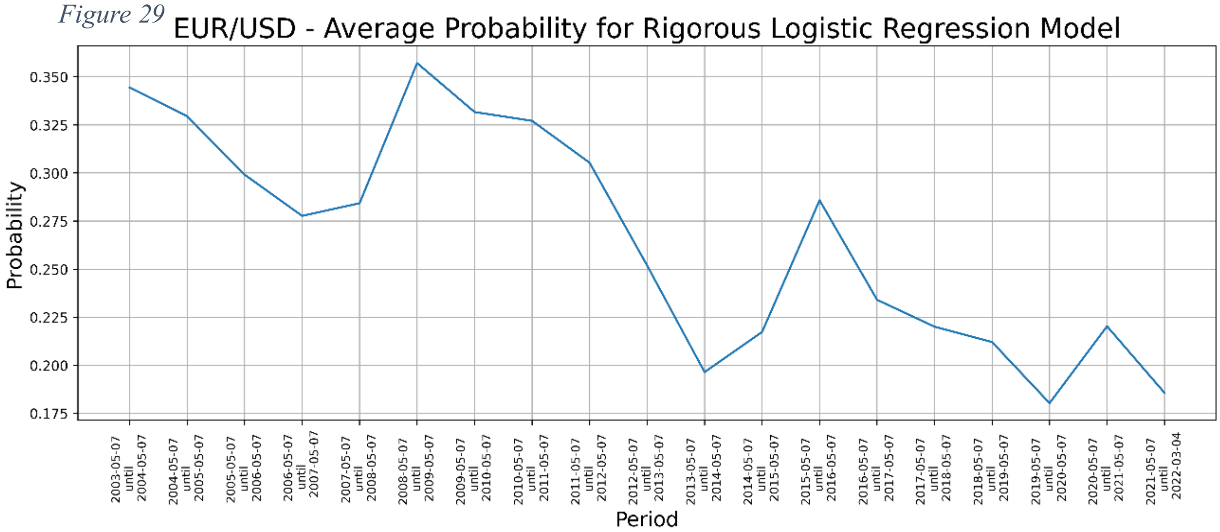
As expected, due to a higher training label HPR threshold, the probabilities corresponding to all percentiles decreased in relation to the Regular Logistic regression model (page 30, Figure 17).

The drop in these percentiles was not as sharp for the second decade of prediction.

For the second decade, the 99.99 percentile rarely surpassed the probability threshold of the model (60%), explaining the extremely low values of percentage of "buy" positions in Figure 27.

In contrast to the Regular Logistic Regression model, the more rigorous model had its' evolution of average probabilty significantly declined for later time periods (Figure 29).

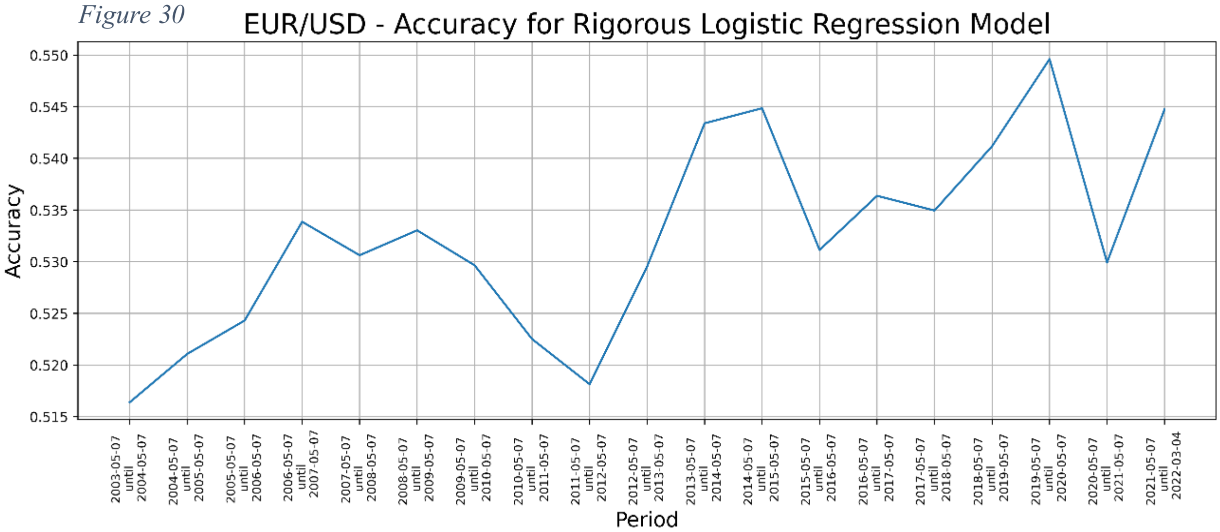
Figure 29



$$Accuracy = \frac{True\ Positives + True\ Negatives}{True\ Positives + False\ Negatives + True\ Negatives + False\ Positives} \approx 0.5322$$

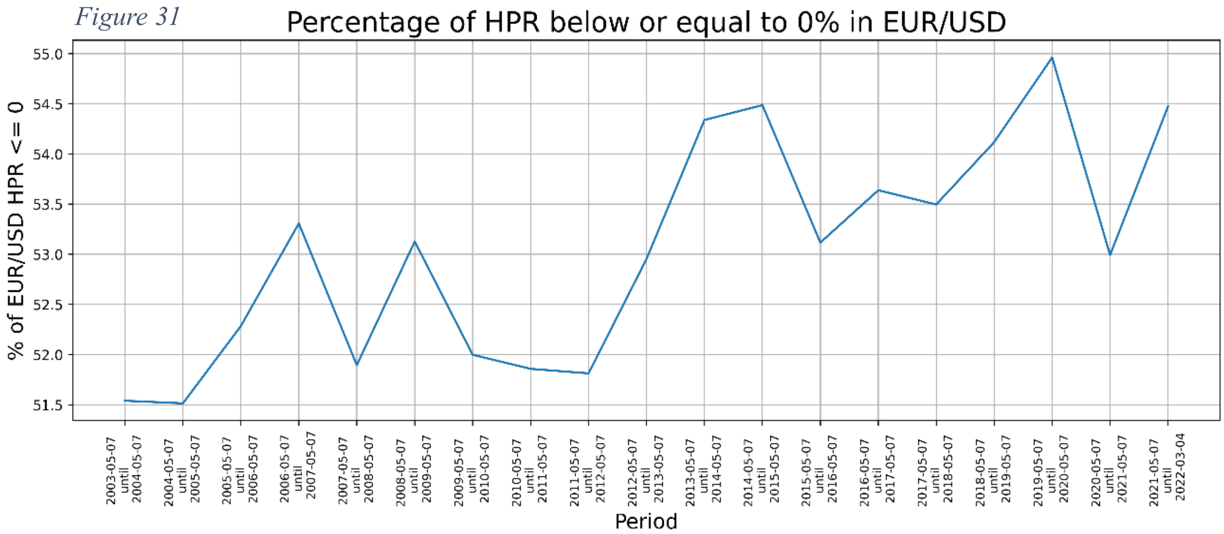
Instead of a moderately constant accuracy, like the one observed for the Regular Logistic Regression model (page 31, Figure 19), this metric increased along the prediction period (Figure 30).

Figure 30



This result is expected and has the following explanation: Since a decreasing number of EUR/USD HPR above 0.6 basis points is observed (Figure 26), and the model is decreasing substantially its confidence when predicting (Figure 28), this causes the model to predict a "buy" position in very rare instances (Figure 27), therefore the accuracy should be highly correlated with the increasing number of negative HPR for later time-periods (Figure 31).

Figure 31



As it is possible to observe, accuracy for the second decade of prediction (Figure 30) is almost completely explained by the percentage of HPR below or equal to 0% in EUR/USD (Figure 31). In fact, for periods where the percentage of "buy" predictions is extremely small, accuracy interpretation is completely irrelevant.

4.2.1.1 Strategy Performance Before Transaction Costs

Table 7

Rigorous Logistic Regression Strategy Performance Before Transaction Costs		
Performance Metric	**Strategy EUR/USD**	**EUR/USD currency exchange rate**
Average Annualized HPR	14.2336%	0.2959%
Annualized Volatility	0.8522%	9.9700%
Sharpe Ratio	16.7027	0.0297
Cumulative Return	1481.8300%	-3.8272%
Evolution of Wealth	15.8183	0.9617

Before transaction costs, the performance of the regular logistic regression model (page 32, Table 2) surpasses the rigorous model (Table 7) in terms of Average Annualized HPR, Sharpe Ratio and Cumulative Return.

Although this is the case, the Rigorous Logistic Regression Model has a much lower volatility than the 2.2365% observed for the regular logistic regression model. The reason is an even lower percentage of periods the model is long on the underlying currency exchange rate (Figure 16 compared with Figure 27).

As presented in Table 7, before TC, this model surpassed in all metrics a strategy comprised of holding the EUR/USD currency pair during the entire prediction period. However, the purpose of the rigorous model is wealth creation for the investor, after TC.

4.2.1.2 Strategy Performance After Transaction Costs

Table 8

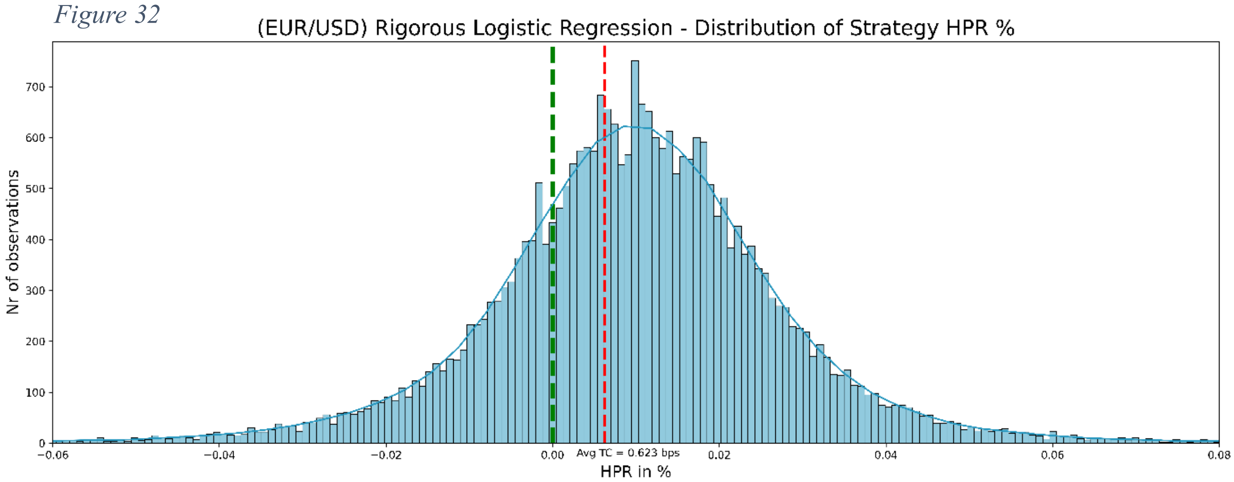
Rigorous Logistic Regression Strategy Performance After Transaction Costs		
Performance Metric	**Strategy EUR/USD**	**EUR/USD currency exchage rate**
Average Annualized HPR	1.6840%	0.2959%
Annualized Volatility	0.7641%	9.9700%
Sharpe Ratio	2.2032	0.0297
Cumulative Return	38.5561%	-3.8272%
Evolution of Wealth	1.385561	0.9617

From the Evolution of Wealth results in Table 8, investing 1 monetary unit in this strategy at 2003-05-07 21:03:00, would increase the wealth to 1.385561 monetary units at the end of the prediction period (compared to 0.9617 if holding the EUR/USD).

A Sharpe Ratio of 2.2032 is also an excellent achievement (e.g., comparing with 0.75 for the S&P 500 during the same time-period).

When observing the distribution of this strategy HPR (Figure 32), we can identify that the adversity that inspired the creation of the Rigorous Model was corrected (see page 34, Figure 20).

Figure 32



This strategy outperformed the EUR/USD currency exchange rate after Transaction Costs.

However, in Table 9, a completely different picture is shown when presenting the evolution of the performance metrics of Table 8.

Table 9

Rigorous Logistic Regression Strategy Performance After Transaction Costs (EUR/USD)				
Period	**Annualized HPR (%)**	**Annualized Volatility (%)**	**Sharpe Ratio**	**Evolution of Wealth**
2003-05-07 21:03:00 - 2004-05-07 21:03:00	-3.465	0.748	-4.634	0.965
2004-05-07 21:03:00 - 2005-05-07 21:03:00	12.891	1.419	9.082	1.142
2005-05-07 21:03:00 - 2006-05-07 21:03:00	-2.968	0.878	-3.379	0.970
2006-05-07 21:03:00 - 2007-05-07 21:03:00	-2.316	0.803	-2.883	0.976
2007-05-07 21:03:00 - 2008-05-07 21:03:00	4.315	1.323	3.260	1.046
2008-05-07 21:03:00 - 2009-05-07 21:03:00	-3.297	0.924	-3.567	0.966
2009-05-07 21:03:00 - 2010-05-07 21:03:00	20.539	1.657	12.392	1.237
2010-05-07 21:03:00 - 2011-05-07 21:03:00	7.220	1.207	5.982	1.077
2011-05-07 21:03:00 - 2012-05-07 21:03:00	-0.644	0.256	-2.511	0.993
2012-05-07 21:03:00 - 2013-05-07 21:03:00	-0.175	0.073	-2.404	0.998
2013-05-07 21:03:00 - 2014-05-07 21:03:00	0.080	0.045	1.778	1.001
2014-05-07 21:03:00 - 2015-05-07 21:03:00	-0.061	0.079	-0.776	0.999
2015-05-07 21:03:00 - 2016-05-07 21:03:00	-0.351	0.257	-1.367	0.996
2016-05-07 21:03:00 - 2017-05-07 21:03:00	0.007	0.068	0.109	1.000
2017-05-07 21:03:00 - 2018-05-07 21:03:00	-0.090	0.045	-2.010	0.999
2018-05-07 21:03:00 - 2019-05-07 21:03:00	-0.015	0.011	-1.403	1.000
2019-05-07 21:03:00 - 2020-05-07 21:03:00	-0.057	0.049	-1.167	0.999
2020-05-07 21:03:00 - 2021-05-07 21:03:00	0.007	0.015	0.472	1.000
2021-05-07 21:03:00 - 2022-03-04 21:30:00	-0.011	0.015	-0.724	1.000

Using this strategy, the investor was able to obtain substantial positive HPR for some periods during the first decade of prediction. When the model does not have sufficient confidence, it does not implement a long position, therefore, in periods when the observed confidence probabilities were lower, the model does not trade as much and did not lose much wealth.

After observing these promising results, it is important to research if this was just a fluke or if this process yields systematic predictability across different currency exchange rates.

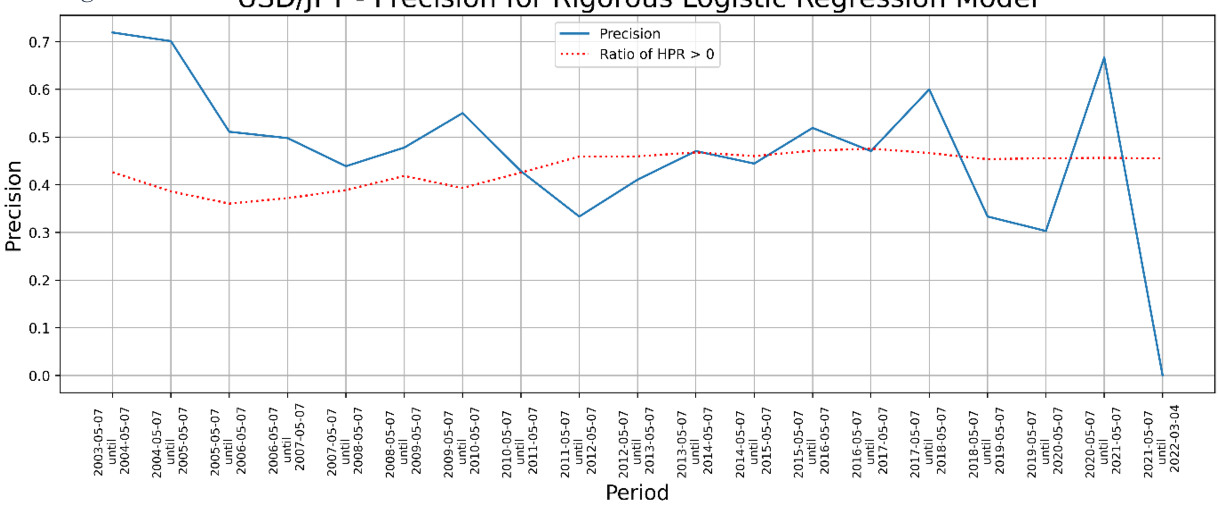
Since the outcomes of the Rigorous Logistic Regression model applied to USD/JPY and GBP/CHF presented very similar conclusions and results to the model applied to EUR/USD, the interpretation of these models will be largely simplified, and auxiliary information will be presented in the appendix.

4.2.2 USD/JPY

Figure 33 shows the evolution of precision (overall precision was 70.1%, comparing with 74.15% for EUR/USD).

Precision was above 70% for the first two periods, but quickly fell to 51.11% the following period and then remained around the ratio of positive USD/JPY HPR.

Figure 33

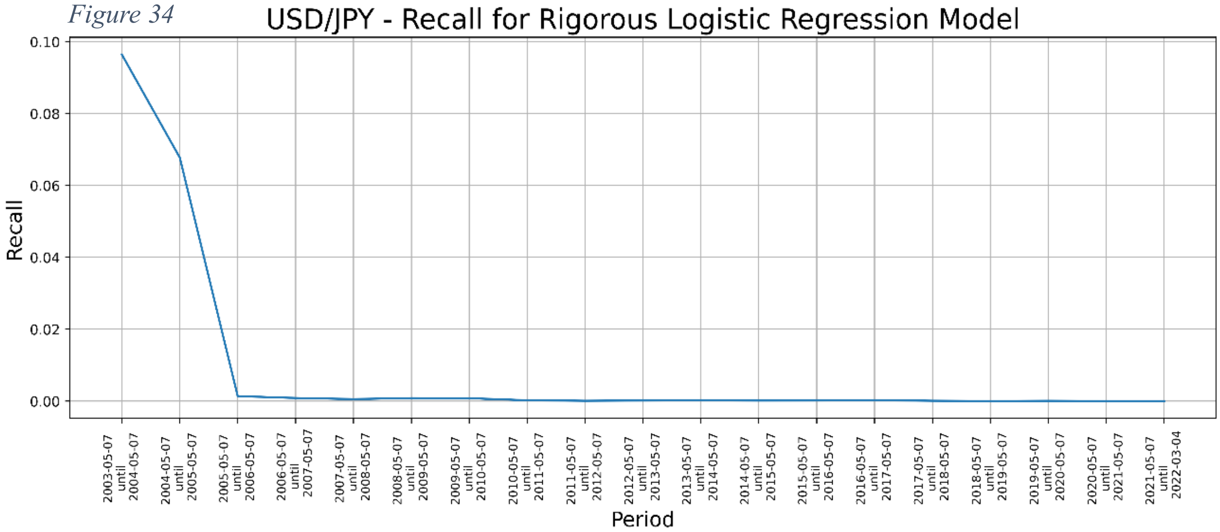


Although precision was relatively high for some later periods, the model made very few predictions, resulting in a small sample of True Positives and False Positives (appendix, Figures III and IX), making the precision values for these periods less reliable.

As we shall see in Figure 34, recall also declined substantially, indicating a decreasing model confidence when predicting. The strategy's wealth creation capability comes only from these two first years of predictability. This seems to be a similar pattern than the one observed for EUR/USD but happening approximately 5 years prematurely.

Figure 34 presents the evolution of Recall (overall recall was 0.83%, comparing to 0.63% when applied to EUR/USD).

Figure 34



Recall was surprisingly high in the first 2 periods (9.64% and 6.775% consecutively), but sharply fell to 0.136% in the third period and continued to decrease to practically 0 the following periods. The recall and precision of the last period was 0, this was because the model only implemented a single "buy" prediction and a negative HPR for USD/JPY was observed (appendix, Figures III and IX).

After implementing the same exact process of analysis as done for the EUR/USD currency pair, we reach the same conclusions. The decrease in recall was caused by both a decrease in overall predictability and confidence of the model.[15] The explanation for this decrease comes from the loss of confidence in prediction. The model cannot find a linear combination of the technical analysis inputs that explain HPR above 0.6 bps in a satisfactory manner, therefore it barely yields probabilities above 60% and rarely implements a long position (appendix, Figure VI and VII).

[15] See figures III to IX in the appendix.

4.2.2.1 Strategy Performance After Transaction Costs

Table 10

Rigorous Logistic Regression Strategy Performance After Transaction Costs			
Performance Metric	**Strategy USD/JPY**	**USD/JPY currency exchage rate**	**Strategy EUR/USD**
Average Annualized HPR	18.0331%	0.5298%	1.6840%
Annualized Volatility	1.2144%	10.9352%	0.7641%
Sharpe Ratio	14.8856	0.0485	2.2032
Cumulative Return	3175.2380%	-1.3100%	38.5561%
Evolution of Wealth	32.7524	0.9869	1.385561

From the Evolution of Wealth, one monetary unit using this strategy from period 2003-05-07 until 2022-03-04 would transform into 32.7524 monetary units.

This strategy substantially outperformed the USD/JPY currency exchange rate, even after TC.

The following table presents the above presented performance metrics for each yearly interval, after transaction costs.

Table 11

Rigorous Logistic Regression Strategy Performance After Transaction Costs (USD/JPY)				
Period	**Annualized HPR (%)**	**Annualized Volatility (%)**	**Sharpe Ratio**	**Evolution of Wealth**
2003-05-07 21:03:00 - 2004-05-07 21:03:00	265.218	4.020	65.981	13.814
2004-05-07 21:03:00 - 2005-05-07 21:03:00	102.669	3.164	32.447	2.875
2005-05-07 21:03:00 - 2006-05-07 21:03:00	-3.960	0.510	-7.762	0.960
2006-05-07 21:03:00 - 2007-05-07 21:03:00	-2.048	0.290	-7.059	0.979
2007-05-07 21:03:00 - 2008-05-07 21:03:00	-2.273	0.308	-7.385	0.977
2008-05-07 21:03:00 - 2009-05-07 21:03:00	-4.406	0.762	-5.784	0.955
2009-05-07 21:03:00 - 2010-05-07 21:03:00	-1.530	0.426	-3.591	0.984
2010-05-07 21:03:00 - 2011-05-07 21:03:00	-1.044	0.274	-3.814	0.989
2011-05-07 21:03:00 - 2012-05-07 21:03:00	-0.587	0.135	-4.359	0.994
2012-05-07 21:03:00 - 2013-05-07 21:03:00	-0.585	0.164	-3.558	0.994
2013-05-07 21:03:00 - 2014-05-07 21:03:00	-0.313	0.267	-1.174	0.997
2014-05-07 21:03:00 - 2015-05-07 21:03:00	-0.161	0.113	-1.430	0.998
2015-05-07 21:03:00 - 2016-05-07 21:03:00	-0.172	0.137	-1.258	0.998
2016-05-07 21:03:00 - 2017-05-07 21:03:00	-0.771	0.561	-1.374	0.992
2017-05-07 21:03:00 - 2018-05-07 21:03:00	-0.102	0.077	-1.323	0.999
2018-05-07 21:03:00 - 2019-05-07 21:03:00	0.017	0.054	0.305	1.000
2019-05-07 21:03:00 - 2020-05-07 21:03:00	-0.682	0.299	-2.284	0.993
2020-05-07 21:03:00 - 2021-05-07 21:03:00	-0.016	0.012	-1.329	1.000
2021-05-07 21:03:00 - 2022-03-04 21:30:00	-0.016	0.015	-1.088	1.000

Using this strategy, the investor was able to obtain substantial positive HPR during the first two periods of prediction. As explained before, when the model does not have sufficient confidence, it does not implement a long position, therefore, in periods when the observed confidence probabilities were lower, the model does not trade as much and did not lose significant wealth.

During the periods from 2005-05-07 until 2010-05-07, as observed in Figure VII, in the appendix, the model still presented relatively high probabilities, causing the model to make "buy" predictions that did not materialize in positive HPR after transaction costs.

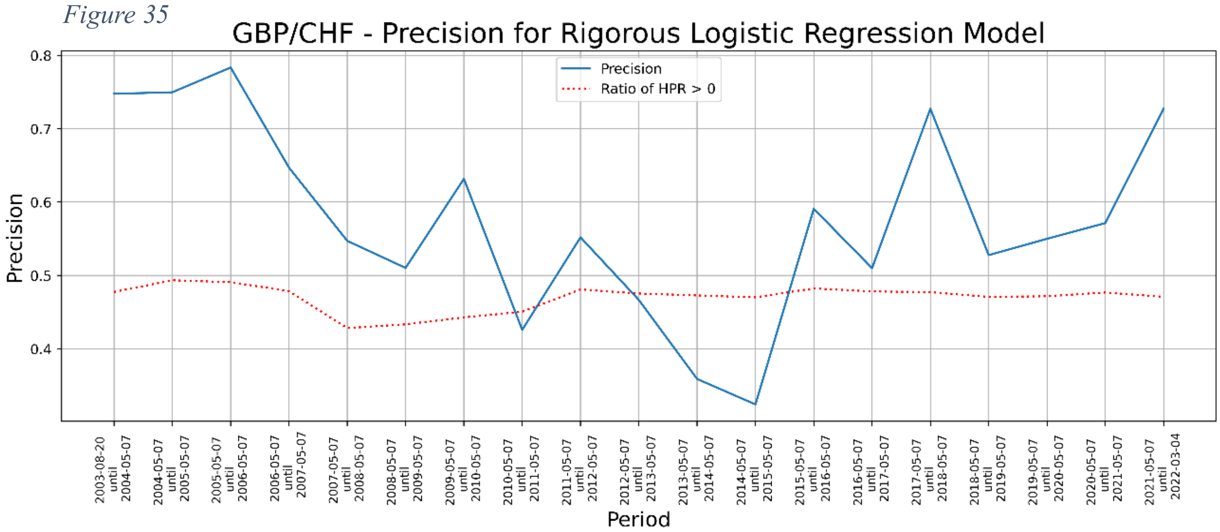
The rigorous logistic regression model fails dramatically when it observes a pattern that works very well in the training set (outputting a high probability), but when applied to the test set, the pattern no longer verifies, or is not able to explain HPR above TC.

In later periods, a huge decrease in percentage of "buy" positions (appendix, Figure VI) caused by lower confidence, turned the model less costly to the investor.

4.2.3 GBP/CHF

Figure 35 shows the evolution of precision (overall precision was 74.76%, compared with 74.16% for EUR/USD).

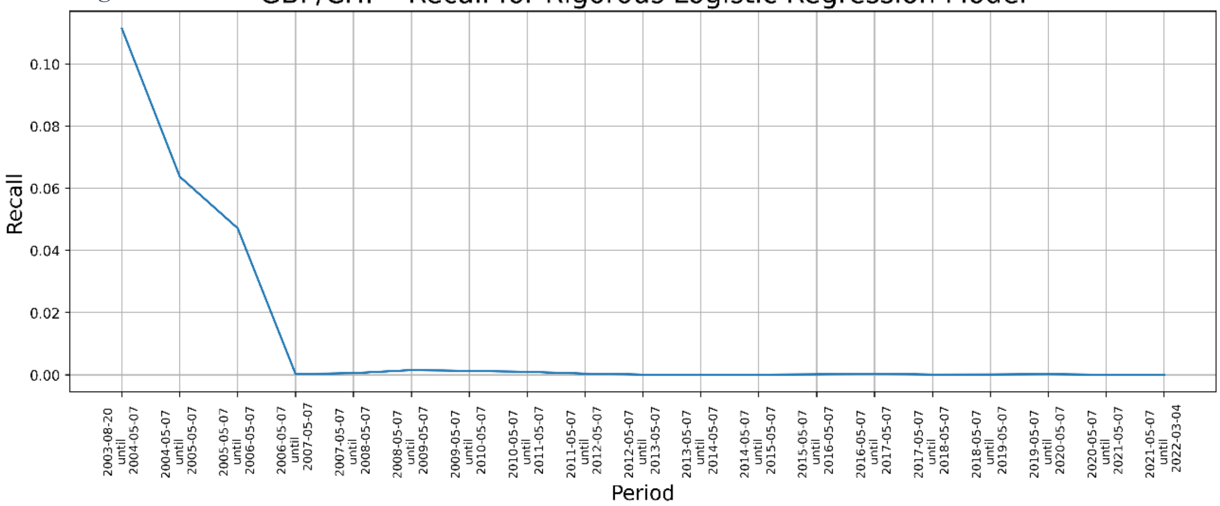
Figure 35



Although precision was relatively high for later periods, the model made very few predictions, resulting in a small sample of True Positives and False Positives (appendix, Figures XI and XVI), making the precision values for later periods less reliable.

Figure 36 shows the evolution of recall (overall recall was 1.09%)

Figure 36

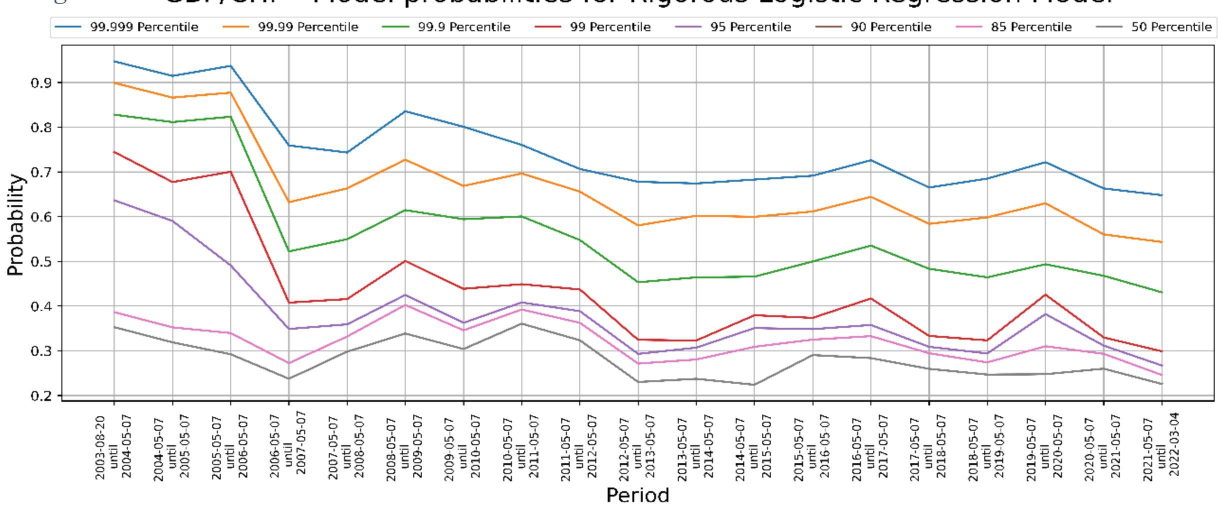


Recall was relatively high in the first 3 periods but, like the results observed in the other currency pairs, this was not sustained, and this measure fell sharply to practically 0.

After implementing the usual analysis, we reach the same conclusions as before.[16] The causing force behind the sudden decrease in recall was a substantial loss of confidence and predictability capacity.

As before, the percentage of "buy" predictions implemented by the model (appendix, Figure XIV), are strongly correlated with recall (Figure 36). A decreasing certainty of the model can also be observed when analyzing the logistic regression's probability outputs evolution, where we see a sudden drop during the transition period between 2005 and 2007 (Figure 37). After, the 99.9 percentile rarely crosses the probability threshold of the model (60%).

Figure 37



[16] See figures XI to XVI in the appendix.

4.2.3.1 Strategy Performance After Transaction Costs

Table 12

Rigorous Logistic Regression Strategy Performance After Transaction Costs				
Performance Metric	**Strategy GBP/CHF**	**GBP/CHF currency exchage rate**	**Strategy EUR/USD**	**Strategy USD/JPY**
Average Annualized HPR	0.8207%	-2.4133%	1.6840%	18.0331%
Annualized Volatility	1.3679%	12.0647%	0.7641%	1.2144%
Sharpe Ratio	0.6000	-0.2000	2.2032	14.8856
Cumulative Return	16.7659%	-45.1164%	38.5561%	3175.2380%
Evolution of Wealth	1.1677	0.5488	1.385561	32.7524

From the Evolution of Wealth, one monetary unit using this strategy from period 2003-08-20 until 2022-03-04 would transform into 1.1677 monetary units.

This strategy, although less profitable than when applied to the other currency pairs, it substantially outperformed the GBP/CHF currency exchange rate.

Table 13 describes the evolution of the above presented performance metrics throughout the prediction period, after transaction costs.

Table 13

Rigorous Logistic Regression Strategy Performance After Transaction Costs (GBP/CHF)				
Period	**Annualized HPR (%)**	**Annualized Volatility (%)**	**Sharpe Ratio**	**Evolution of Wealth**
2003-08-20 09:56:00 - 2004-05-07 21:03:00	273.049	5.433	50.261	7.396
2004-05-07 21:03:00 - 2005-05-07 21:03:00	-76.275	2.445	-31.195	0.456
2005-05-07 21:03:00 - 2006-05-07 21:03:00	-44.382	1.810	-24.514	0.633
2006-05-07 21:03:00 - 2007-05-07 21:03:00	-0.917	0.140	-6.532	0.991
2007-05-07 21:03:00 - 2008-05-07 21:03:00	-3.503	0.374	-9.356	0.964
2008-05-07 21:03:00 - 2009-05-07 21:03:00	-22.822	1.451	-15.732	0.789
2009-05-07 21:03:00 - 2010-05-07 21:03:00	-7.184	0.575	-12.484	0.928
2010-05-07 21:03:00 - 2011-05-07 21:03:00	-8.907	0.676	-13.173	0.912
2011-05-07 21:03:00 - 2012-05-07 21:03:00	-4.607	0.577	-7.977	0.953
2012-05-07 21:03:00 - 2013-05-07 21:03:00	-0.667	0.147	-4.524	0.993
2013-05-07 21:03:00 - 2014-05-07 21:03:00	-0.771	0.152	-5.061	0.992
2014-05-07 21:03:00 - 2015-05-07 21:03:00	-1.518	0.319	-4.757	0.985
2015-05-07 21:03:00 - 2016-05-07 21:03:00	-0.761	0.190	-4.002	0.992
2016-05-07 21:03:00 - 2017-05-07 21:03:00	-2.455	0.472	-5.197	0.975
2017-05-07 21:03:00 - 2018-05-07 21:03:00	-0.395	0.211	-1.868	0.996
2018-05-07 21:03:00 - 2019-05-07 21:03:00	-0.869	0.317	-2.741	0.991
2019-05-07 21:03:00 - 2020-05-07 21:03:00	-2.563	0.551	-4.655	0.974
2020-05-07 21:03:00 - 2021-05-07 21:03:00	-0.176	0.074	-2.371	0.998
2021-05-07 21:03:00 - 2022-03-04 21:30:00	-0.093	0.036	-2.587	0.999

Using this strategy, the investor was only able to obtain substantial positive HPR for the first period of prediction. Here, it is evident one of the big downsides one might face when using this strategy. The model presented remarkably high probabilities from 2003-08-20 until 2006-05-07 (Figure 37), but these did not reflect well the behavior of the prediction set, after TC. This caused the model to make a considerably high percentage of "buy" decisions (appendix,

Figure XIV) that did not materialize in a sufficiently high positive HPR that covered the Bid-Ask Spread.

In other words, the linear relationships that the model detected between the TA explanatory variables and HPR of GBP/CHF, didn't materialize into profit when applied to the test set. This caused the model to sustain a high amount of losses (after TC), during the second and third period of prediction (Table 13).

This could also be indicative that the model is having overfitting problems. Overfitting is a consequence of overtraining the model in the train set. When the model performs excess training, it might just "memorize" the training data, and therefore has inferior results when trying to generalize the behavior to predict in the test set.

Another explanation could be the much higher average proportional Bid-Ask Spread observed for GBP/CHF (Table 1). This value was 2.23 bps, compared to 0.615 for EUR/USD and 0.845 for USD/JPY.

To pinpoint the cause, the evolution of the performance metrics is presented before transaction costs (Table 14).

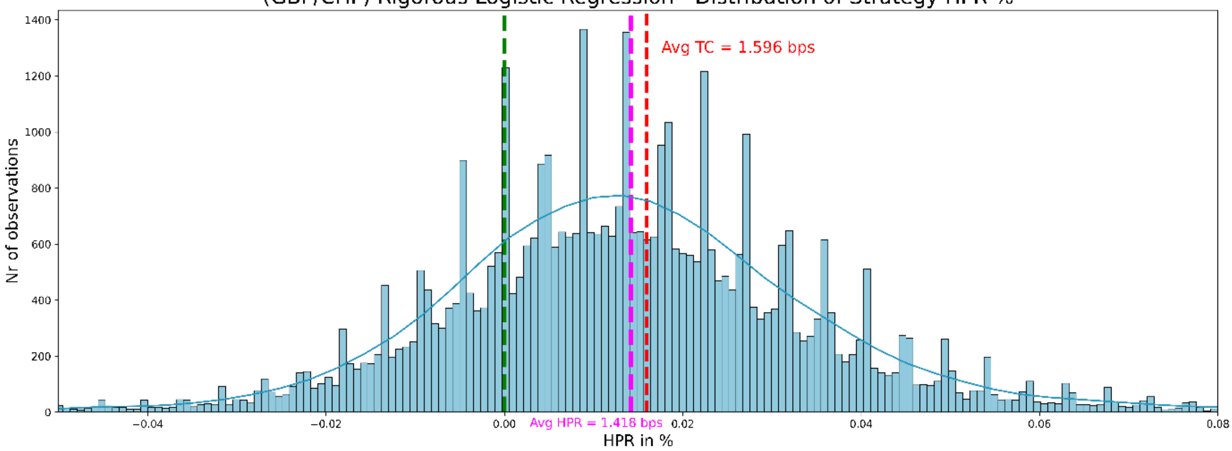
Table 14

Rigorous Logistic Regression Strategy Performance Before Transaction Costs (GBP/CHF)				
Period	**Annualized HPR (%)**	**Annualized Volatility (%)**	**Sharpe Ratio**	**Evolution of Wealth**
2003-08-20 09:56:00 - 2004-05-07 21:03:00	459.621	5.562	82.630	29.045
2004-05-07 21:03:00 - 2005-05-07 21:03:00	183.703	2.872	63.971	6.633
2005-05-07 21:03:00 - 2006-05-07 21:03:00	141.051	2.277	61.957	4.282
2006-05-07 21:03:00 - 2007-05-07 21:03:00	0.247	0.091	2.701	1.003
2007-05-07 21:03:00 - 2008-05-07 21:03:00	0.455	0.192	2.370	1.005
2008-05-07 21:03:00 - 2009-05-07 21:03:00	0.882	0.843	1.046	1.009
2009-05-07 21:03:00 - 2010-05-07 21:03:00	2.170	0.418	5.195	1.023
2010-05-07 21:03:00 - 2011-05-07 21:03:00	0.175	0.471	0.370	1.002
2011-05-07 21:03:00 - 2012-05-07 21:03:00	-0.208	0.309	-0.673	0.998
2012-05-07 21:03:00 - 2013-05-07 21:03:00	-0.002	0.070	-0.031	1.000
2013-05-07 21:03:00 - 2014-05-07 21:03:00	-0.087	0.078	-1.112	0.999
2014-05-07 21:03:00 - 2015-05-07 21:03:00	-0.259	0.149	-1.736	0.997
2015-05-07 21:03:00 - 2016-05-07 21:03:00	0.204	0.120	1.708	1.002
2016-05-07 21:03:00 - 2017-05-07 21:03:00	-0.044	0.170	-0.258	1.000
2017-05-07 21:03:00 - 2018-05-07 21:03:00	0.092	0.087	1.053	1.001
2018-05-07 21:03:00 - 2019-05-07 21:03:00	-0.171	0.203	-0.840	0.998
2019-05-07 21:03:00 - 2020-05-07 21:03:00	0.064	0.200	0.318	1.001
2020-05-07 21:03:00 - 2021-05-07 21:03:00	0.020	0.056	0.349	1.000
2021-05-07 21:03:00 - 2022-03-04 21:30:00	0.091	0.038	2.388	1.001

From the previous table, it is observable that the Rigorous Logistic Regression model produced excellent results, before TC, during August 2003 until May 2006 (compared to holding GBP/CHF presented in appendix, Table VIII). As mentioned before, in the following periods, the model saw a huge decrease in predictability capacity. Therefore, it seems the cause of significant losses observed in Table 13 was due to the model correctly predicting positive HPR, but not sufficiently high to cover the proportional Bid-Ask Spread.

Figure 38 presents the distribution of the strategy's HPR from 2003-08-20 until 2006-05-07.

Figure 38



As it is possible to observe, during the period that the model presented predictability, the average strategy HPR (magenta vertical line) was substantially positive but could not cover the average proportional Bid-Ask spread, for the same time-period. This is indicative that the biggest cause of model implementation failure, was the high TC presented in this currency pair.

However, once again, the strategy seems to have provided relevant HPR predictability, OOS for some periods of implementation during the first decade of the 21st century.

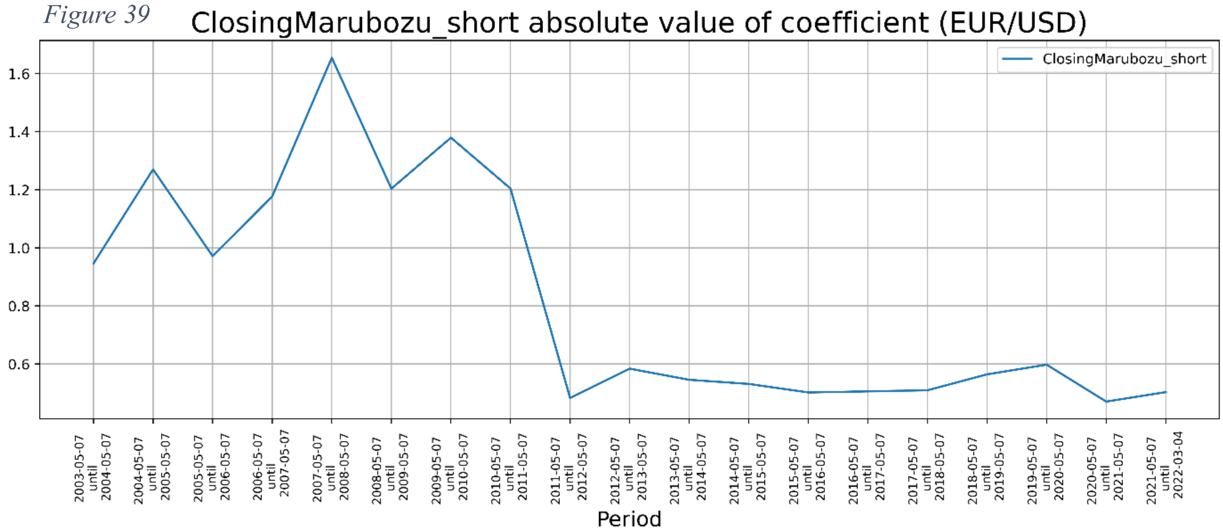
4.3 Final Remarks

All Rigorous Logistic Regression models presented predictability of HPR during some periods in the first decade of the 21st century. This small section attempts to pinpoint which technical indicators created this predictability and their associated coefficients evolution.

The several combinations of 5 features, chosen by the feature selection model, that yielded probabilities above 90% were retrieved and analyzed. The features responsible of yielding these probabilities for the three currency exchange rates are presented in tables II, III and IV in the appendix. When omitting these features, all models lose their capacity of generating profitability after TC.

For all studied models, the top explanatory variables that had the highest amount of explanatory power over HPR, saw their coefficients decrease. The explanatory variable that presented, by a substantial margin, in all analyzed currency exchange pairs, the highest predictive capacity of HPR was the “ClosingMarubozu_short”. As an example, Figure 39 shows the evolution of the absolute value of its coefficient for the EUR/USD currency pair.

Figure 39

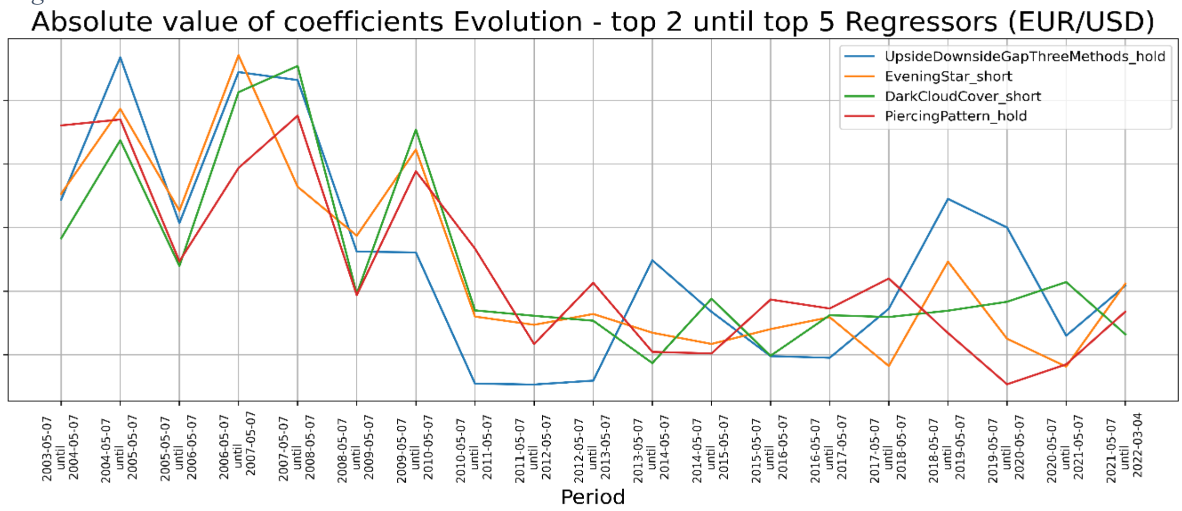


This regressor presented a huge decrease in predictability, exactly when the EUR/USD Rigorous Logistic Regression model stopped being profitable (page 46, Table 9).

The coefficients associated with the other top explaining regressors also saw a decreasing tendency.

Figure 40 presents the top 5 absolute value of regression coefficients evolution for EUR/USD, except for the ClosingMarubozu_short (already presented in Figure 39). There is a clear downward trend. This shows further evidence that the coefficients that used to explain HPR ceased to do so.

Figure 40



This same pattern was also observed in the models applied to the other currencies.

There was some variation in the quantity of detection of these technical patterns throughout the prediction period, but this was not correlated with the decrease/increase in the coefficients, neither with the probability outputs of the model.

5 Conclusion

To assess the meaningfulness of the results it is necessary to look at the overall economic context during this analysis period. Since the financial crisis of 2007-2008 the European Central Bank (ECB) and the Federal Reserve (FED) entered an extensive Quantitative Easing (QE) program, injecting enormous amounts of currency in the economy. This directly increases the money supply and artificially manipulates currency prices. The evolution of QE can be visualized through the progression of total assets owned by central banks.

Figure 41. Sources: Board of Governors; BoJ; BoE; ECB | current active Link: myf.red/g/nJKO

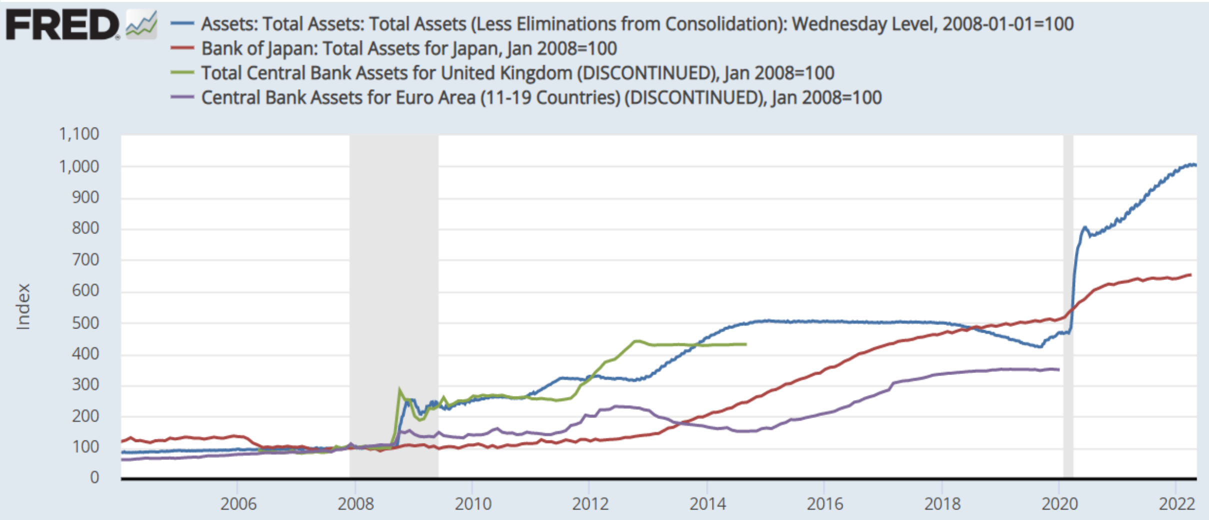
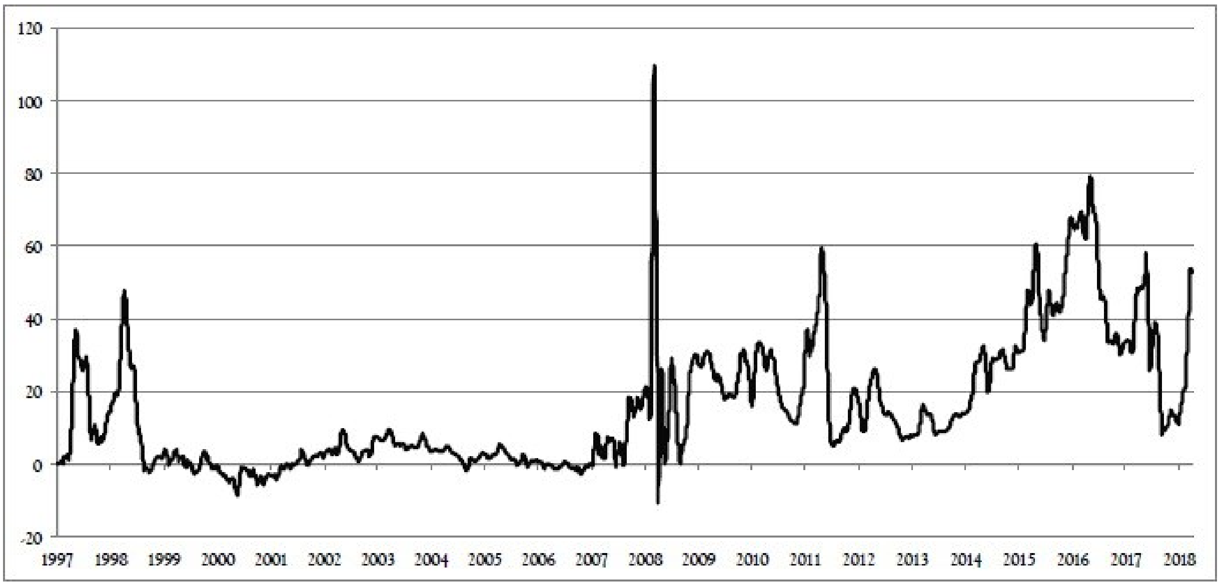


Figure 41 was retrieved from FRED[17] and represents the evolution in total assets of the FED (in blue), Bank of Japan (in red), Bank of England (in green) and ECB (in violet). We can see a massive increase in QE after the 2007-2008 financial crisis on all 4 presented economies, and that this was uncorrelated with the precision and confidence of all models presented.

[17] FRED current active link: https://fred.stlouisfed.org/graph/?g=PinJ. The sources used to construct Figure 41 were: Board of Governors of the Federal Reserve System (US), Bank of Japan, Bank of England and European Central Bank (complementary referencing presented in the References section).

Another important event that happened during the analysis period was the observation of Covered Interest rate Parity (CIP) deviations both in EUR/USD and USD/JPY.[18] Figure 42 was retrieved from Stenfors (2019) and is relative to 3-month CIP deviations (in bps) in the USD/JPY currency exchange rate.

Figure 42. Source: Stenfors (2019) - Covered Interest rate Parity Deviations (USD/JPY)



It is possible to observe that Figure 42 presents no correlation with the confidence of the Rigorous Logistic Regression model applied to the USD/JPY (appendix, Figure VII), neither with the precision of this same model (page 47, Figure 33). The same was observed for EUR/USD.

All developed models showed promising predictability during some periods in the first decade of the 21st century. These where very basic in their implementation and only used technical patterns observed in the previous minute as explanatory variables.

From this research, it is impossible to assess what is the cause of this predictability and we are left with more questions than answers.

It is also remarkably sinister the sudden loss in prediction from the models. As seen in section 4.3, the absolute value of the coefficients associated with the TA regressors showed a

[18] According to Borio et al. (2016), "*CIP is the closest thing to a physical law in international finance*" (p. 45). The CIP is an equation that represents an equilibrium condition between currency exchange rates. When deviations from this equation appear, arbitrage becomes possible. Violations of CIP have been an important indicator of stress in the international financial system (Stenfors, 2019).

decreasing tendency during the prediction period. This is another indication that patterns that used to be good predictors of positive HPR stopped being reliable.

Unfortunately, the author was not able to find minute data from periods before May 2003 to assess if this predictability was present.

One possible reason behind the decrease in HPR predictability could be the recent massive increase in automated high-frequency trading using machine learning algorithms.

As Olson (2004) states, *"The existence of significant trading rule profits appears to contradict market efficiency, but perhaps such returns only represent a temporary inefficiency that is corrected once market participants become aware of it"* (p. 86).

Several studies report TA trading strategies with declining profitability. For example, Marsh (2000) estimates two-state Markov models and shows that the performance of these previously profitable trading rules dramatically declined in the 1990s.

Even so, a more enigmatic result from this dissertation is left unanswered. An increasing market efficiency is incapable of explaining why the EUR/USD model lost its prediction capacity much after the USD/JPY and GBP/CHF.

This study however, demonstrated that until 2011 (page 46, Table 9) for the EUR/USD currency exchange rate, using only technical analysis patterns as inputs, a very basic machine learning linear classifier presented evidence of HPR predictability. Similar shorter-lived results are also observed for both USD/JPY and GBP/CHF. This was then successfully transformed in a wealth creating strategy, after TC. This gives hope to more sophisticated machine learning algorithms and the use of technical patterns for profitable trading.

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Appendix

Figure I – Definitions of all technical patterns used from Lo et al. (2000).

All following technical patterns are characterized by a sequence of five consecutive local extrema $E_1, \ldots, E_5$:

Head and Shoulders (HS)

$$HS = \begin{cases} E_1 \text{ is a maximum} \\ E_3 > E_1,\ E_3 > E_5 \\ E_1 \text{ and } E_5 \text{ are within 1.5 percent of their average} \\ E_2 \text{ and } E_4 \text{ are within 1.5 percent of their average} \end{cases}$$

Inverse Head and Shoulders (IHS)

$$IHS = \begin{cases} E_1 \text{ is a minimum} \\ E_3 < E_1,\ E_3 < E_5 \\ E_1 \text{ and } E_5 \text{ are within 1.5 percent of their average} \\ E_2 \text{ and } E_4 \text{ are within 1.5 percent of their average} \end{cases}$$

Broadening Tops (BTOPS)

$$BTOPS = \begin{cases} E_1 \text{ is a maximum} \\ E_1 < E_3 < E_5 \\ E_2 > E_4 \end{cases}$$

Broadening Bottoms (BBOT)

$$BBOT = \begin{cases} E_1 \text{ is a minimum} \\ E_1 > E_3 > E_5 \\ E_2 < E_4 \end{cases}$$

Triangle Tops (TTOPS)

$$TTOPS = \begin{cases} E_1 \text{ is a maximum} \\ E_1 > E_3 > E_5 \\ E_2 < E_4 \end{cases}$$

Triangle Bottoms (TBOT)

$$TBOT = \begin{cases} E_1 \text{ is a minimum} \\ E_1 < E_3 < E_5 \\ E_2 > E_4 \end{cases}$$

Rectangle Tops (RTOP)

$$RTOP = \begin{cases} E_1 \text{ is a maximum} \\ \text{tops are within 0.75 percent of their average} \\ \text{bottoms are within 0.75 percent of their average} \\ \text{lowest top} > \text{highest bottom} \end{cases}$$

Rectangle Bottoms (RBOT)

$$RBOT = \begin{cases} E_1 \text{ is a minimum} \\ \text{tops are within 0.75 percent of their average} \\ \text{bottoms are within 0.75 percent of their average} \\ \text{lowest top} > \text{highest bottom} \end{cases}$$

Table I – The 61 Candlestick Patterns retrieved from TA-Lib

Two Crows	Upside Downside Gap Three Methods
Three Black Crows	On Neck Pattern
Three Inside Up Down	Homing Pigeon
Three Line Strike	Identical Three Crows
Three Outside Up Down	In Neck Pattern
Three Stars In The South	Inverted Hammer
Three Advancing White Soldiers	Kicking
Abandoned Baby	Kicking bull bear determined by the longer marubozu
Advance Block	Ladder Bottom
Belthold	Long Legged Doji
Breakaway	Long Line Candle
Closing Marubozu	Marubozu
Concealing Baby Swallow	Matching Low
Counterattack	Mat Hold
Dark Cloud Cover	Morning Doji Star
Doji	Morning Star
Doji Star	Piercing Pattern
Dragonfly Doji	Rickshaw Man
Engulfing Pattern	Rising Falling Three Methods
Evening Doji Star	Separating Lines
Evening Star	Shooting Star

up/down-gap side-by-side white lines	Short Line Candle
Gravestone Doji	Spinning Top
Hammer	Stalled Pattern
Hanging Man	Stick Sandwich
Harami Pattern	Takuri Dragonfly Doji with very long lower shadow
Harami Cross Pattern	Tasuki Gap
High Wave Candle	Thrusting Pattern
Hikkake Pattern	Tristar Pattern
Modified Hikkake Pattern	Unique 3 River
Upside Gap Two Crows	

Table II – Explanatory variables that produced a probability above 90% for EUR/USD

ThreeOutsideUpDown_short	Hammer_hold
HikkakePattern_StrongShort	ShortLineCandle_hold
EngulfingPattern_short	LongLineCandle_short
InNeckPattern_short	InvertedHammer_hold
ClosingMarubozu_short	Marubozu_short
ThreeInsideUpDown_short	HangingMan_short
Marubozu_hold	StickSandwich_hold
LongLineCandle_hold	EveningStar_short
ClosingMarubozu_hold	GravestoneDoji_hold
UpsideDownsideGapThreeMethods_hold	ThrustingPattern_short
DarkCloudCover_short	TasukiGap_hold
PiercingPattern_hold	ThreeLineStrike_hold
ModifiedHikkakePattern_hold	

Table III - Explanatory Variables that produced a probability above 90% for USD/JPY

ClosingMarubozu_short	DojiStar_short
LongLineCandle_short	BTOPS
ClosingMarubozu_hold	DojiStar_hold
Marubozu_short	HighWaveCandle_hold
AdvanceBlock_short	ThreeOutsideUpDown_short
ThreeInsideUpDown_short	BBOT
GravestoneDoji_hold	EngulfingPattern_short
HangingMan_short	HighWaveCandle_short
EveningStar_short	HikkakePattern_long
InvertedHammer_hold	HikkakePattern_short
DarkCloudCover_short	PiercingPattern_hold
HikkakePattern_StrongShort	RTOP
Hammer_hold	ThrustingPattern_short
OnNeckPattern_short	TristarPattern_short
SeparatingLines_short	UpDowngapsidebysidewhitelines_hold
Counterattack_short	

Table IV - Explanatory Variables that produced a probability above 90% for GBP/CHF

ClosingMarubozu_short	UpsideDownsideGapThreeMethods_hold
HikkakePattern_StrongShort	EveningDojiStar_short
ClosingMarubozu_hold	PiercingPattern_hold
EveningStar_short	ThreeOutsideUpDown_short
InvertedHammer_hold	Counterattack_short
Marubozu_short	DarkCloudCover_short
LongLineCandle_short	MorningDojiStar_hold
ThreeInsideUpDown_short	MorningStar_hold
GravestoneDoji_hold	ShortLineCandle_short
HangingMan_short	StickSandwich_hold
InNeckPattern_short	TasukiGap_hold
RTOP	TasukiGap_short
EngulfingPattern_short	DojiStar_short
SeparatingLines_short	HikkakePattern_long
UpDowngapsidebysidewhitelines_short	SeparatingLines_hold
RBOT	ThreeInsideUpDown_hold
StalledPattern_short	ThrustingPattern_short

Rigorous Logistic Regression Model – USD/JPY

Figure II

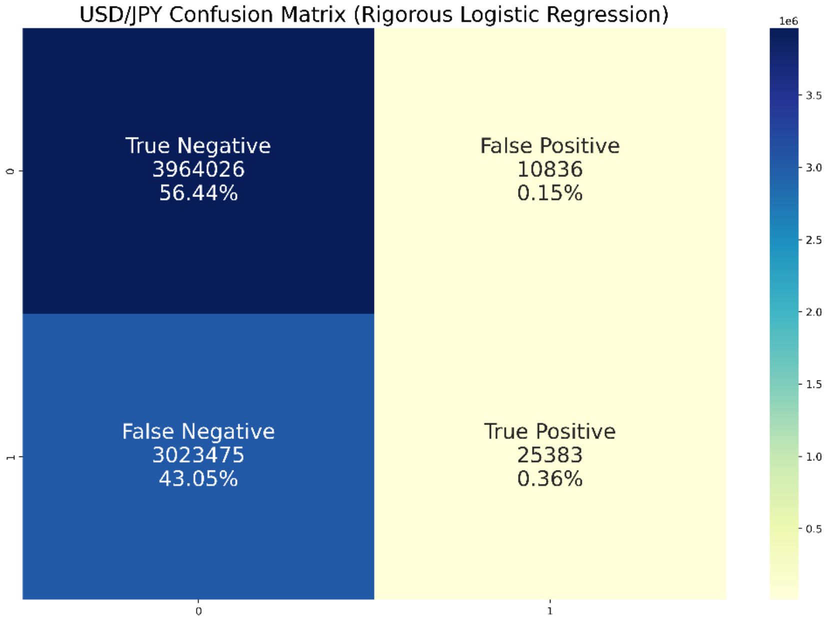

Figure III

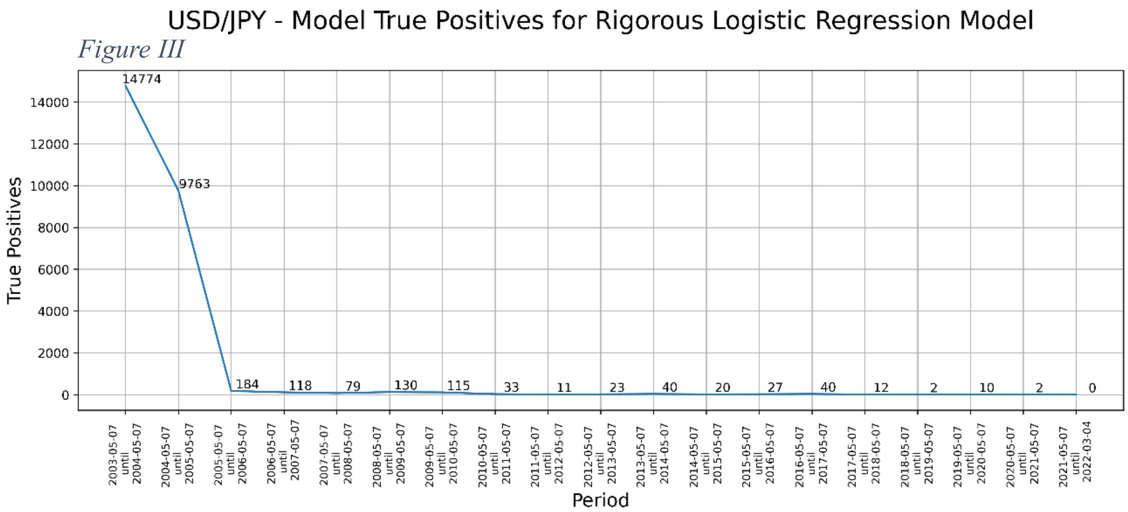

Figure IV

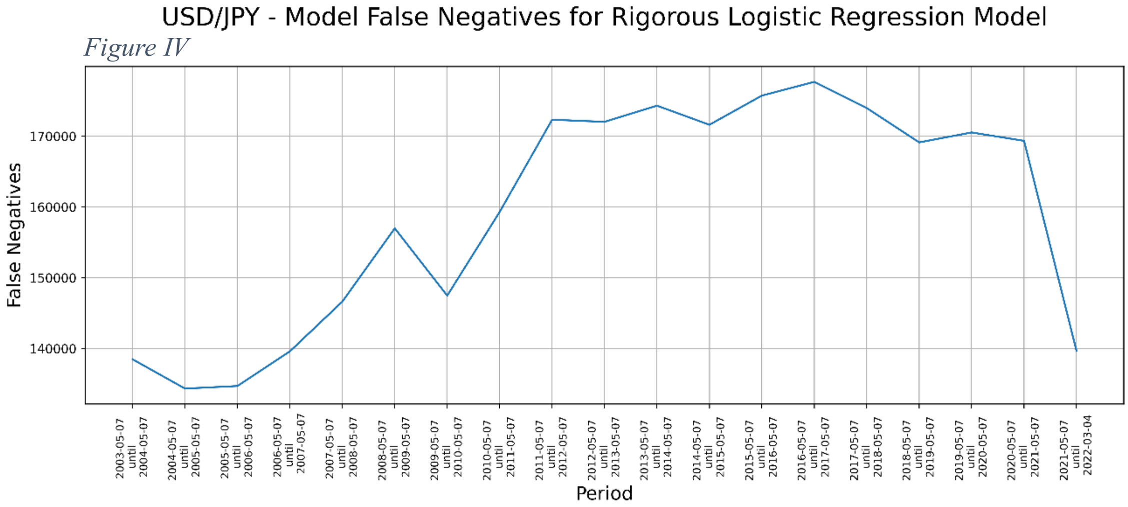

Figure V

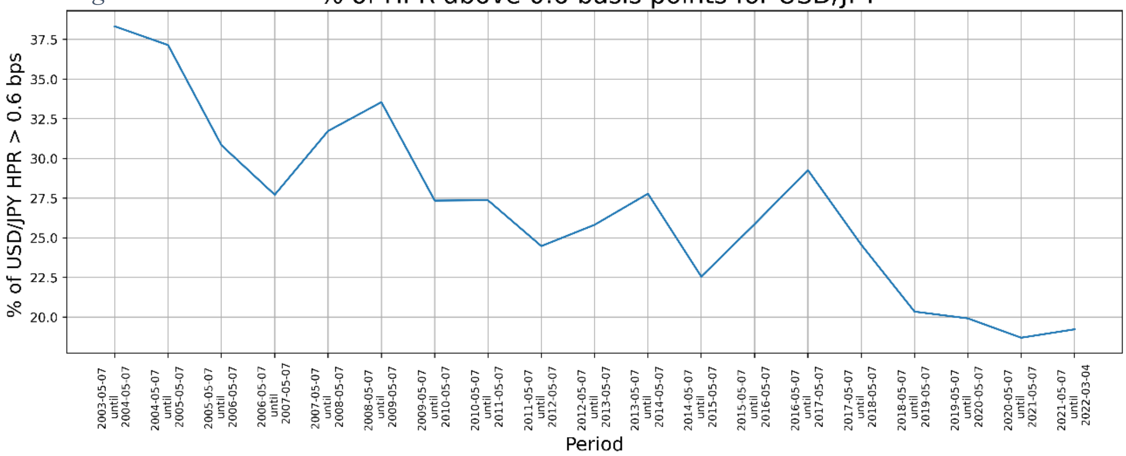

Figure VI

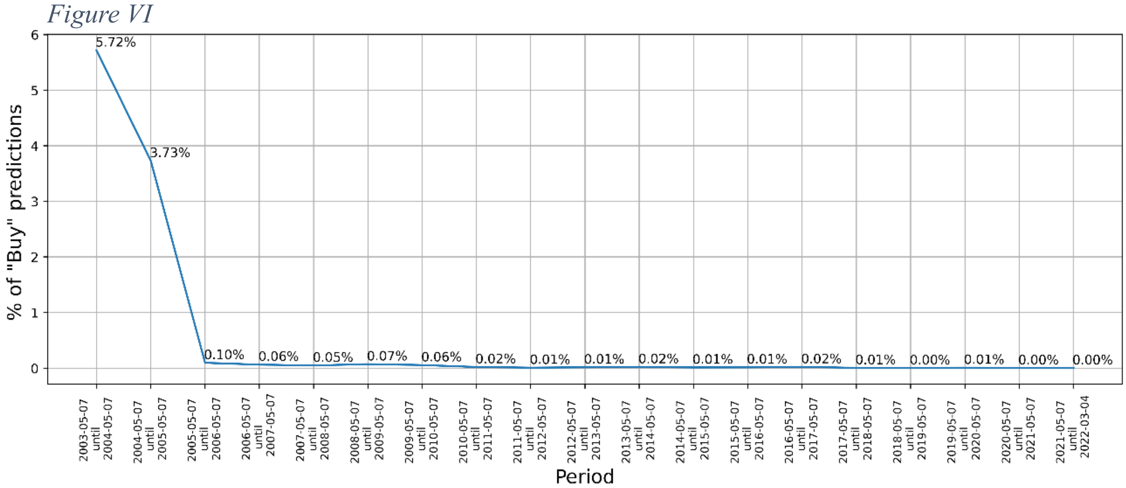

Figure VII

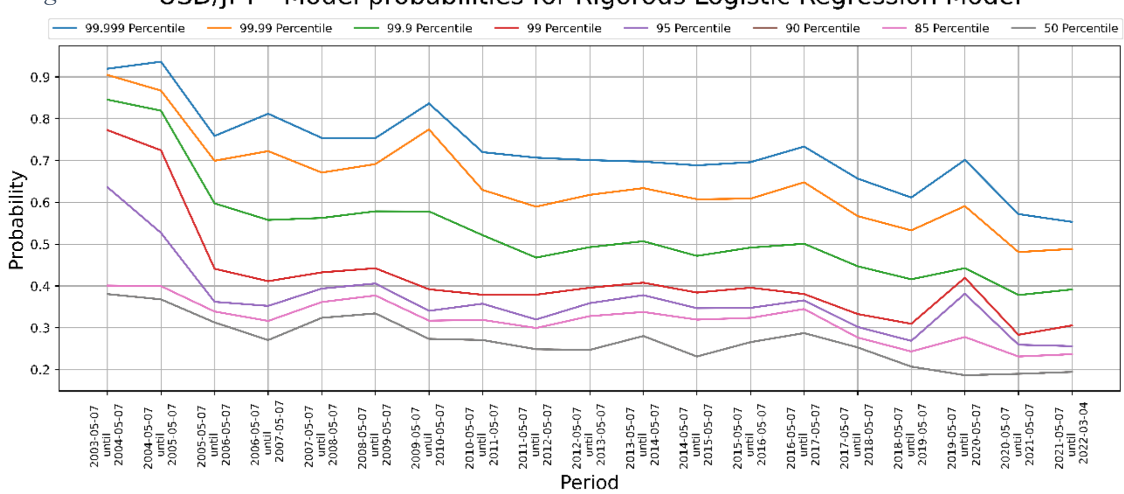

Figure VIII

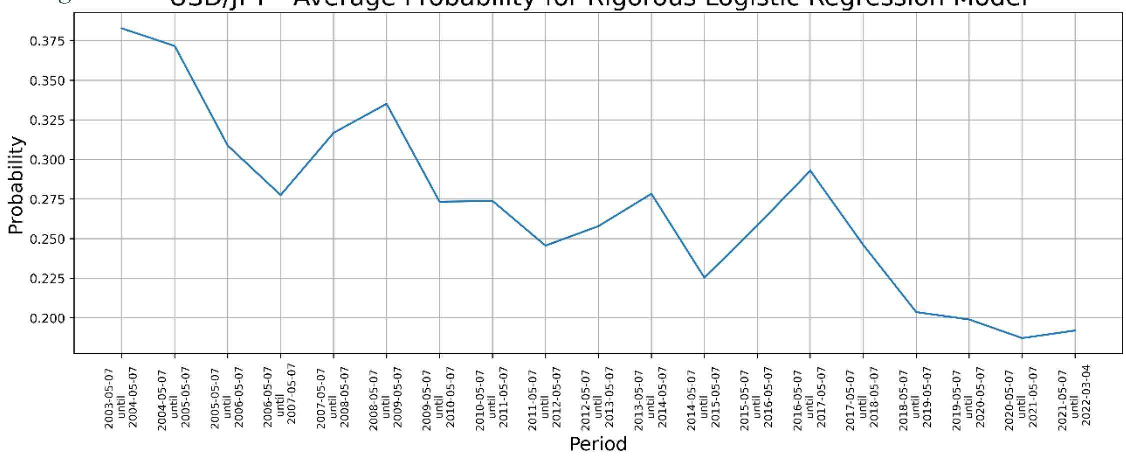

Figure IX

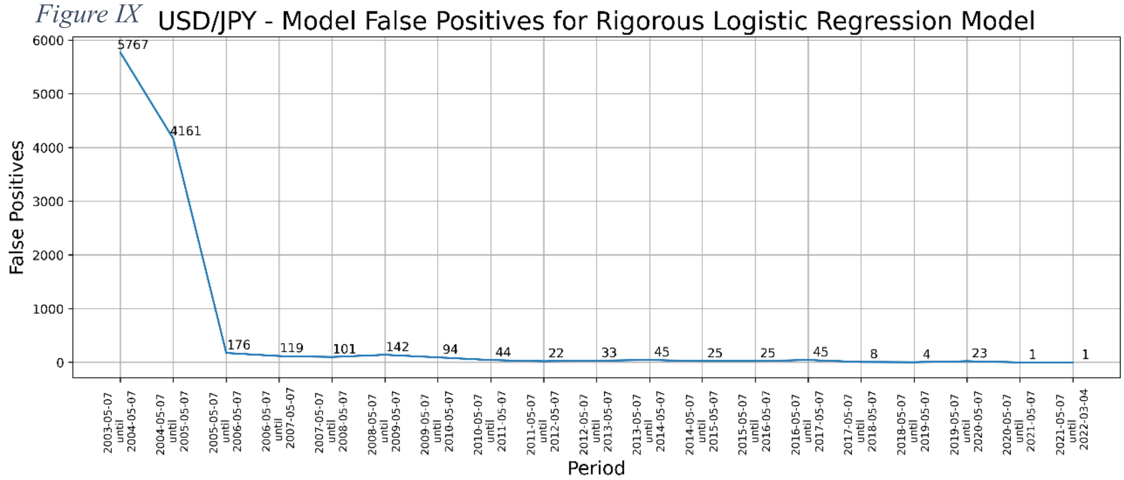

Table V

Rigorous Logistic Regression Strategy Performance Before Transaction Costs			
Performance Metric	Strategy USD/JPY	USD/JPY currency exchage rate	Strategy EUR/USD
Average Annualized HPR	26.8767%	0.5298%	14.2336%
Annualized Volatility	1.2525%	10.9352%	0.8522%
Sharpe Ratio	21.4587	0.0485	16.7027
Cumulative Return	18038.1000%	-1.3100%	1481.8300%
Evolution of Wealth	181.3810	0.9869	15.8183

Table VI

USD/JPY Exchange Rate				
Period	Annualized HPR (%)	Annualized Volatility (%)	Sharpe Ratio	Evolution of Wealth
2003-05-07 21:03:00 - 2004-05-07 21:03:00	-2.658	14.116	0.399	0.964
2004-05-07 21:03:00 - 2005-05-07 21:03:00	-5.562	13.079	0.745	0.936
2005-05-07 21:03:00 - 2006-05-07 21:03:00	6.674	9.688	-0.014	1.066
2006-05-07 21:03:00 - 2007-05-07 21:03:00	7.175	9.176	0.789	1.072
2007-05-07 21:03:00 - 2008-05-07 21:03:00	-12.422	12.579	1.373	0.872
2008-05-07 21:03:00 - 2009-05-07 21:03:00	-3.385	19.057	-0.743	0.948
2009-05-07 21:03:00 - 2010-05-07 21:03:00	-6.794	13.002	-0.372	0.924
2010-05-07 21:03:00 - 2011-05-07 21:03:00	-11.667	11.924	0.999	0.880
2011-05-07 21:03:00 - 2012-05-07 21:03:00	-0.449	9.533	-0.723	0.991
2012-05-07 21:03:00 - 2013-05-07 21:03:00	21.238	9.640	0.066	1.239
2013-05-07 21:03:00 - 2014-05-07 21:03:00	3.394	10.655	0.881	1.029
2014-05-07 21:03:00 - 2015-05-07 21:03:00	16.020	8.424	-2.078	1.175
2015-05-07 21:03:00 - 2016-05-07 21:03:00	-10.236	10.107	0.158	0.895
2016-05-07 21:03:00 - 2017-05-07 21:03:00	5.916	12.654	-0.326	1.054
2017-05-07 21:03:00 - 2018-05-07 21:03:00	-3.046	8.004	1.066	0.966
2018-05-07 21:03:00 - 2019-05-07 21:03:00	1.207	6.533	-0.841	1.010
2019-05-07 21:03:00 - 2020-05-07 21:03:00	-3.199	8.499	-0.390	0.964
2020-05-07 21:03:00 - 2021-05-07 21:03:00	2.310	5.798	1.647	1.022
2021-05-07 21:03:00 - 2022-03-04 21:30:00	6.753	5.748	-1.981	1.057

Rigorous Logistic Regression Model – GBP/CHF

Figure X

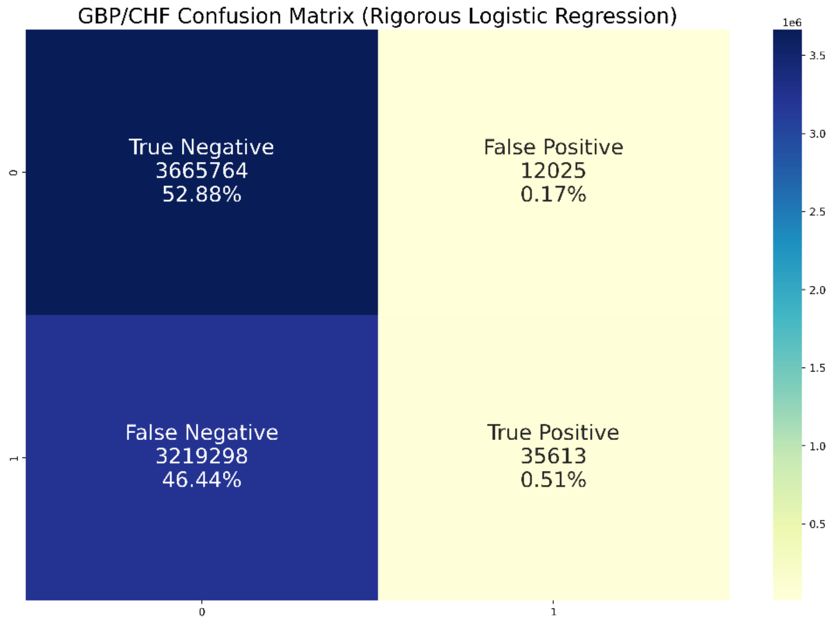

Figure XI

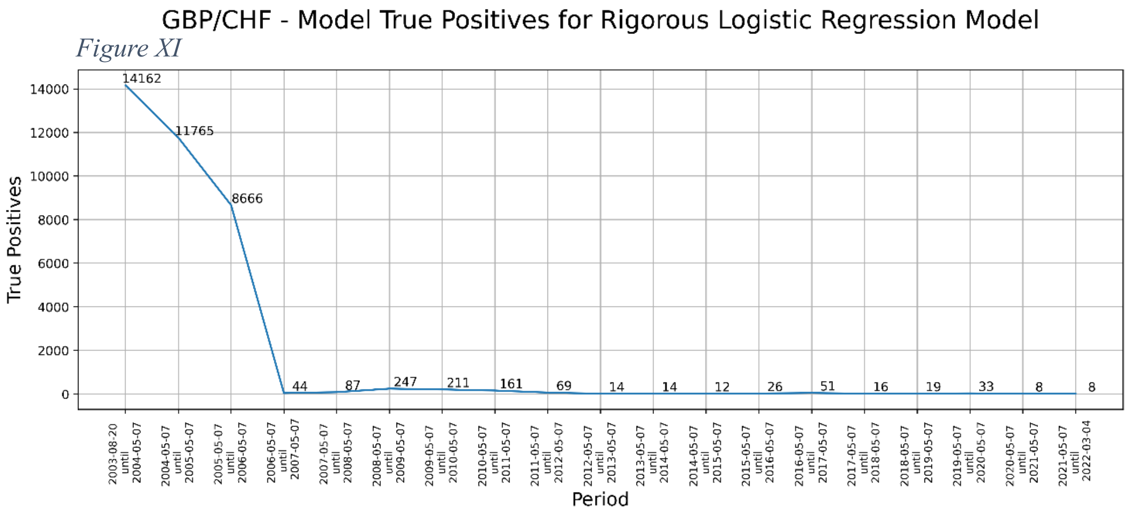

Figure XII

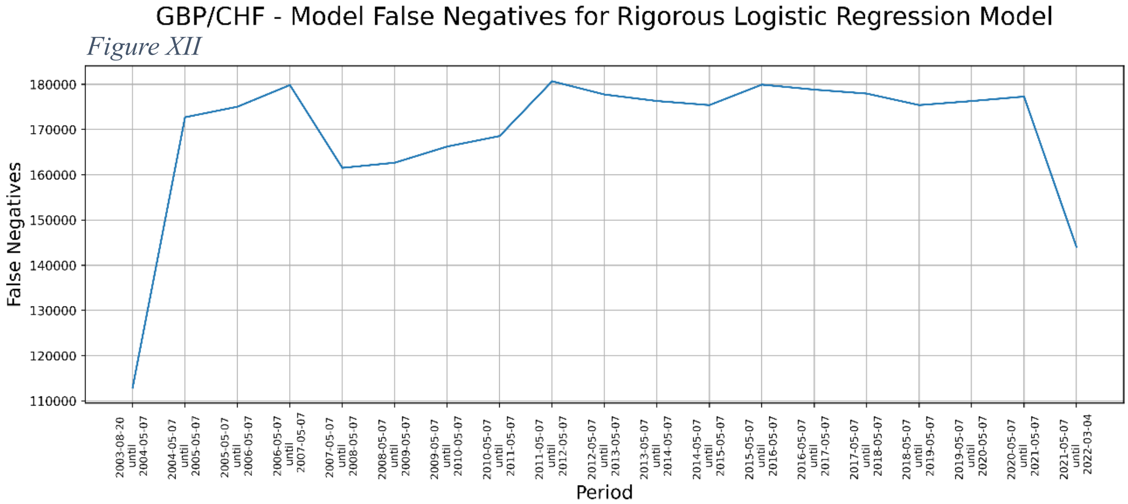

Figure XIII

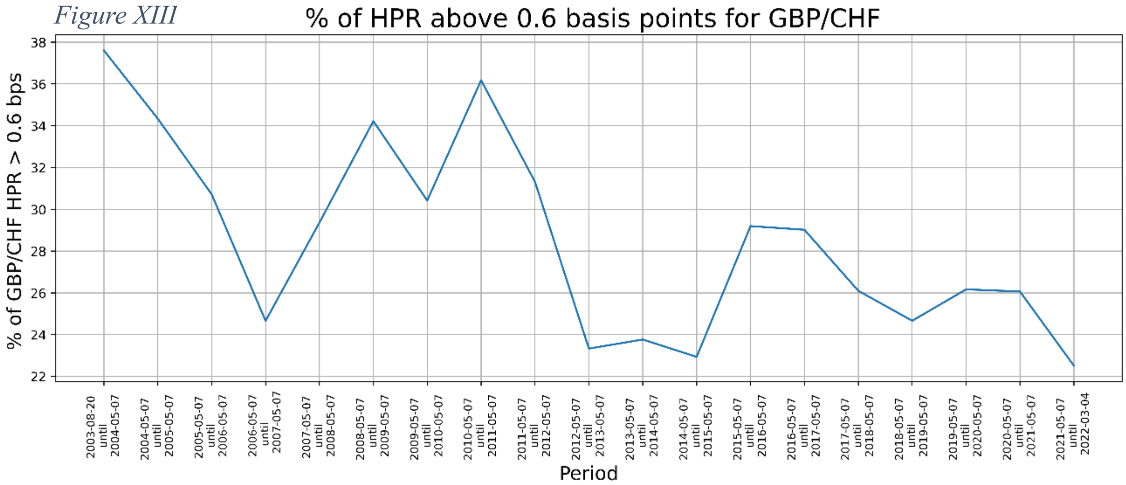

Figure XIV

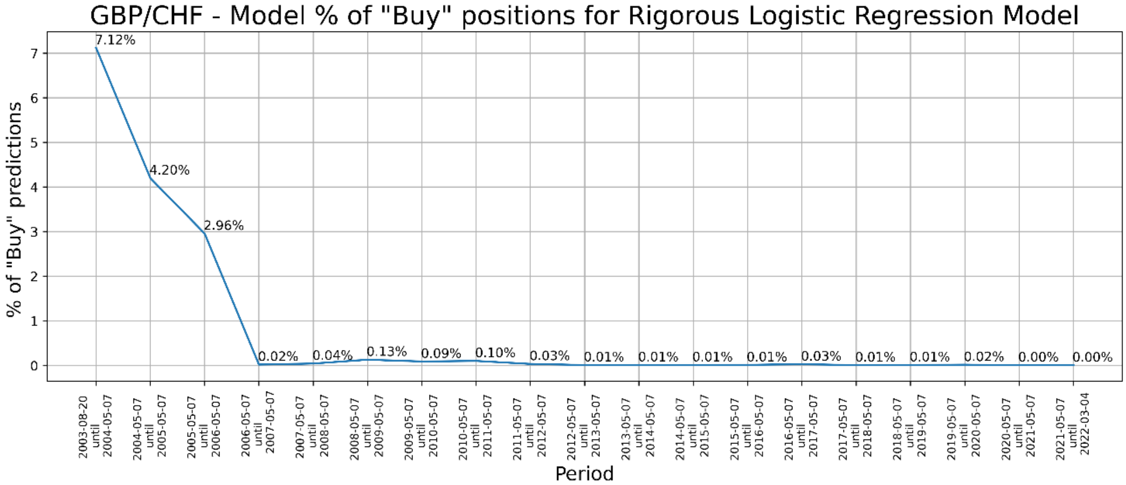

Figure XV

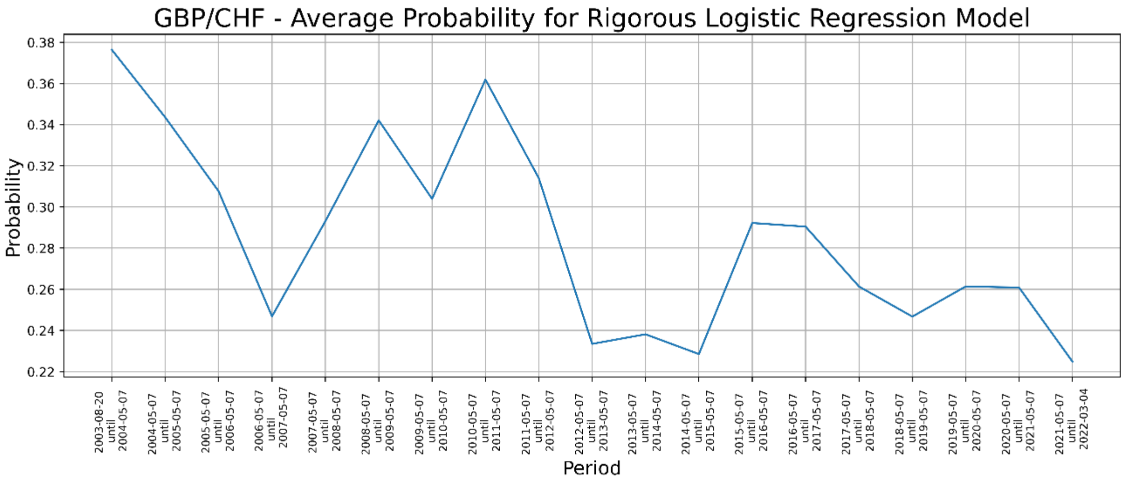

Figure XVI

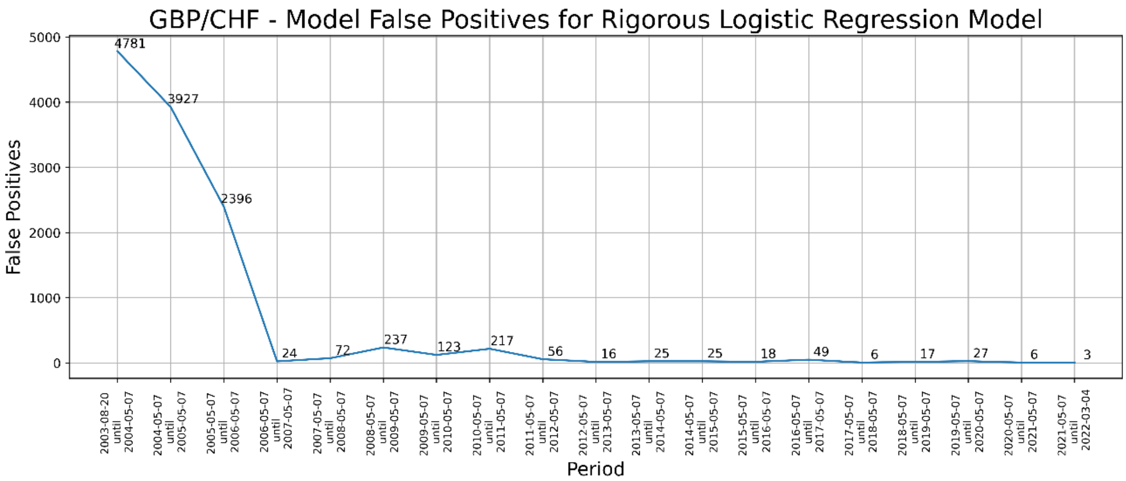

Table VII

Rigorous Logistic Regression Strategy Performance Before Transaction Costs				
Performance Metric	**Strategy GBP/CHF**	**GBP/CHF currency exchage rate**	**Strategy EUR/USD**	**Strategy USD/JPY**
Average Annualized HPR	35.2552%	-2.4133%	14.2336%	26.8767%
Annualized Volatility	1.4197%	12.0647%	0.8522%	1.2525%
Sharpe Ratio	24.9035	-0.2000	16.7027	21.4587
Cumulative Return	85525.0000%	-45.1164%	1481.8300%	18038.1000%
Evolution of Wealth	856.2500	0.5488	15.8183	181.3810

Table VIII

GBP/CHF Exchange Rate				
Period	**Annualized HPR (%)**	**Annualized Volatility (%)**	**Sharpe Ratio**	**Evolution of Wealth**
2003-08-20 09:56:00 - 2004-05-07 21:03:00	8.000	15.582	0.513	1.051
2004-05-07 21:03:00 - 2005-05-07 21:03:00	-1.315	10.499	-0.125	0.981
2005-05-07 21:03:00 - 2006-05-07 21:03:00	0.306	9.099	0.034	0.999
2006-05-07 21:03:00 - 2007-05-07 21:03:00	5.816	7.187	0.809	1.059
2007-05-07 21:03:00 - 2008-05-07 21:03:00	-14.639	10.375	-1.411	0.854
2008-05-07 21:03:00 - 2009-05-07 21:03:00	-16.663	19.750	-0.844	0.825
2009-05-07 21:03:00 - 2010-05-07 21:03:00	-2.687	11.865	-0.226	0.965
2010-05-07 21:03:00 - 2011-05-07 21:03:00	-11.803	13.829	-0.854	0.877
2011-05-07 21:03:00 - 2012-05-07 21:03:00	4.473	14.467	0.309	1.036
2012-05-07 21:03:00 - 2013-05-07 21:03:00	-1.933	8.087	-0.239	0.977
2013-05-07 21:03:00 - 2014-05-07 21:03:00	2.294	8.215	0.279	1.020
2014-05-07 21:03:00 - 2015-05-07 21:03:00	-2.652	18.670	-0.142	0.956
2015-05-07 21:03:00 - 2016-05-07 21:03:00	-0.377	11.744	-0.032	0.989
2016-05-07 21:03:00 - 2017-05-07 21:03:00	-7.761	14.011	-0.554	0.914
2017-05-07 21:03:00 - 2018-05-07 21:03:00	6.054	9.244	0.655	1.060
2018-05-07 21:03:00 - 2019-05-07 21:03:00	-1.490	9.064	-0.164	0.981
2019-05-07 21:03:00 - 2020-05-07 21:03:00	-9.306	11.277	-0.825	0.903
2020-05-07 21:03:00 - 2021-05-07 21:03:00	4.964	9.136	0.543	1.048
2021-05-07 21:03:00 - 2022-03-04 21:30:00	-4.132	7.455	-0.554	0.964