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Abstract

This master thesis focuses on carry, value and momentum factors in currency markets and examines whether machine learning models may prove superior than traditional models in timing factor portfolios. Factor investing has been thoroughly documented in the literature. Nevertheless, growing number of academic research rediscovers machine learning models in an attempt to provide new insights in both well investigated and under researched fields. The paper uses daily data of currency spot and forward exchange rates as well as indices accounting for volatility, liquidity, macroeconomic and capital flows dynamics. The models are trained with moving time windows in order to obtain a single prediction for a next period return. Based on the prediction the factor portfolios are systematically rebalanced. The results suggest that factor timing enhances the performance of the majority of the factors. Moreover, the timed factor portfolios using machine learning algorithms deliver superior risk-return trade-offs in comparison to a logistic regression approach.

Abstrakt

Diese Masterarbeit konzentriert sich auf Carry-, Value- und Momentum in Devisenmärkten und untersucht, ob sich Modelle des maschinellen Lernens beim Timing der Faktoren vorteilhafter gegenüber herkömmlichen Modellen erweisen. Das faktorbasierte Investieren ist in der Literatur ausführlich dokumentiert. Dennoch entdeckt eine wachsende Zahl akademischer Forschungen die Modelle des maschinellen Lernens wieder, um neue Erkenntnisse sowohl in gut untersuchten als auch in wenig erforschten Bereichen zu liefern. Die Masterarbeit verwendet tägliche Daten zu Devisenkassakursen und Devisenterminkursen sowie Indizes, die Volatilität, Liquidität, makroökonomische Dynamik und Kapitalflüsse berücksichtigen. Die Modelle werden mit gleitenden Zeitfenstern trainiert, um eine Vorhersage für die Rendite der nächsten Periode zu erhalten. Basierend auf der Prognose wird das Faktorportfolio neu gewichtet. Die Ergebnisse deuten darauf hin, dass Faktor-Timing die Entwicklung der meisten Faktoren verbessert. Darüber hinaus liefern Algorithmen des maschinellen Lernens eine viel bessere Leistung im Vergleich zu einem logistischen Regressionsansatz.

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List of Abbreviations

API	Application Programming Interface
BCOM	Bloomberg Commodity Index
BEER	Behavioral Equilibrium Exchange Rate
BGN	Bloomberg Generic Price
CAPM	Capital Asset Pricing Model
CPI	Consumer Price Index
DM	Developed markets
EMH	Efficient Market Hypothesis
EM	Emerging markets
ETF	Exchange traded fund
FEER	Fundamental Equilibrium Exchange Rate
FX	Foreign Exchange
GDP	Gross Domestic Product
GMM	Generalized method of moments
GMT	Greenwich Mean Time
IRP	Interest Rate Parity
IV	Instrumental variable
KNN	K-Nearest Neighbors
LSTM	Long Short-Term Memory
MB	Macroeconomic Balance
ML	Machine Learning
NATREX	Natural Real Exchange Rate
NER	Nominal Exchange Rate
NFCI	Chicago Fed National Financial Conditions Index
PEER	Permanent Equilibrium Exchange Rate
PPP	Purchasing Power Parity
REER	Real Effective Exchange Rate
RER	Real Exchange Rate
RF	Random Forest
RNN	Recurrent Neural Network
SVM	Support Vector Machines
VIX	CBOE Volatility Index
VXY	JPMorgan volatility index from G7 currencies

1. Introduction

The utilization of risk factors to explain asset prices in the investment industry can be traced back to the 1960s when Treynor (1961) and Sharpe (1964) were the first to introduce the Capital Asset Pricing Model (CAPM). The CAPM emphasizes the market's undiversifiable risk as the primary driver of asset prices. Fama and French (1992) argue that the CAPM can't fully explain average stock returns due to the influence of diverse company characteristics. They introduce a three-factor asset pricing model, adding size and book-to-market equity as variables to the CAPM equation. The first variable captures the empirical observation that the stock returns of small size companies' stocks are on average higher than those of large companies. The second variable accounts for the systematical outperformance of companies with high book-to-market equity over those with low book-to-market equity value. Fama and French (1992) demonstrate a robust relationship between those factors and the variation in the performance of equity over the broad market, thereby identifying new sources of risk and return. These findings led to increased research in various markets and asset classes. Examples include the corporate bond market (Houweling & Zundert, 2017), currencies, commodities and government bonds as well as Japanese, European and British stock markets (Asness, Moskowitz, & Pedersen, 2013).

1.1. Factor timing

The insights gave rise to a novel investment approach known as factor investing. This method aims at capturing premia associated with the specific risk factors in order to outperform a broad market portfolio. Studies have highlighted the dynamic nature of the different risk factors. Consequently, the concept of factor timing has gained importance. Factor timing refers to the method of rotating factor exposure based on expected changes in the factor risk premia. Haddad, Kozak and Santosh (2020) assert that the performance of equity factors is to some extent predictable. Thus, a portfolio of systematically overweighting factors with higher expected returns has the potential to outperform static factor investing. The research highlights that applying a dynamic approach to factor investing in order to account for the changing nature of the different factor returns over time, can improve investment performance. However, factor timing requires accurate predictions of future returns, which is difficult to achieve consistently and should not even be possible according to the efficient market hypothesis (EMH). The Efficient Market Hypothesis in its weakest form states that one cannot systematically profit

from information about past prices of a security because this information is already reflected in the current price of the security (Fama, 1970).

1.2. Currencies

Aiming to contribute new insights to the field, the current work concentrates on currencies. Since the global financial crisis 2007-2008 due to the zero interest rates environment in some of the major developed economies traditional asset classes have experienced high returns. Ilmanen (2022) argues that the current high asset prices would reduce the realized future returns. Therefore, in the coming years there may be more interest among the investment professionals towards historically proven sources of risk premia but in other, alternative asset classes. Currency based strategies are thought to have low correlations to traditional assets (Binny, 2005). Furthermore, due to the fact that risk factors capture different sources of risk, they are generally unrelated to one another. This is also shown by Asness, Moskowitz and Pedersen (2013), who report low correlation between the currency value and momentum factors. Although one can argue whether currencies can be viewed as an alternative asset class or even be considered as an investment, one can surely trade currencies and implement them in a portfolio both for diversification or in search of harvesting risk premia.

The factors, subject to the research, are defined in the literature as value, momentum and carry. Despite the fact that currency value and momentum haven't been researched as extensively as in other asset classes, there are still studies identifying some of the main drivers behind. The carry factor remains one of the most researched phenomenon on the currency markets. I use these insights in identifying key explanatory variables and go one step further with the intention to extensively examine whether one can use conventional and machine learning methods to time their exposure to the single factor. The input variables are summarized in four main categories – volatility, liquidity, macroeconomics and capital flows.

1.3. Machine learning

With the focus on factor timing within the currency context, the thesis recognizes the unexplored potential of machine learning in this area. Machine learning is an interdisciplinary field that covers the study of computer algorithms, which automate optimization problems (Mitchell, 1997). Building on insights from mathematics, statistics and game theory, the machine learning algorithms use a variety of rules and functions to optimize mathematically defined problems. Most of the approaches rely on iteration in the processing of the data, which

enables the computers to converge towards an optimal solution. The growing popularity in using such algorithms both in academic and business applications advocates for the potential benefit of understanding and incorporating them in research and commerce. The former models are considered to be initially introduced over seven decades ago (Samuel, 1959). This raises the question why their potential haven't been explored until now. One possible explanation is perhaps their inefficiency in providing reasonable output. Another common idea is that computational power was not as cheap and accessible as today, which made it unattractive to entrepreneurs or scholars (Mitchell T. M., 2007). One can form a whole discussion on how machine learning came to be and what potential benefits or risks for the different industries it may hold. There are a few papers, indeed, which discuss this topic. Israel, Kelly and Moskowitz (2020) argue that the asset management industry could not be the best example of a field, which releases the whole potential behind the different machine learning algorithms due to the scarce data and limited application availabilities. In addition, the authors also reason that machine learning is thriving in environments where predictability exists. Forecasting market prices has always been considered as a leading area of interest but also very challenging and even unthinkable. Nevertheless, Israel, Kelly and Moskowitz (2020) also discuss research papers with promising results in predicting stock returns using machine learning models. Example of the use of machine learning models in stock market prediction can also be found in Vijh et al. (2020). Kumbure et al. (2022) lay a literature review of over 130 papers published in journals, which research the implementation of machine learning in a financial market context. The authors also give a summary of some performance indicators of the models, which evaluate their prediction abilities. Several algorithms demonstrate up to 80% correct forecasts. However, most of the papers in the literature focus more on the stock market and use technical and fundamental data as inputs to the models. Furthermore, as Chong, Han and Park (2017) suggest the existing body of literature does not provide a definite answer whether machine learning methods used in predicting returns actually prove superior than a linear approximation approach. As of now machine learning models have hardly been implemented in exploring factor timing on the foreign exchange markets.

1.4. Research questions

The thesis aims to enrich the academic literature by examining whether factor timing of the value, carry and momentum in the currency markets using machine learning models can outperform the static factor. The timing happens by systematically taking long and short positions on the single factor based on the predictions from the models. Second, I question

2. Data and Data preprocessing

whether under identical input variables, machine learning models outperform simple logistic regression.

The thesis provides an exhaustive and transparent data analysis, which eventually may be used by interested academics or practitioners for further experimenting with the used models and input variables.

1.5. Structure

The further outline of the work introduces the data and its preprocessing. In section 3, the focus moves to the factor time series and discusses the way the different factors are constructed for the analysis. Afterwards, section 5 motivates the choice and the logic behind the input variables, which attempt to explain the factor dynamics. Next, in section 6, the construction of the statistical methods is discussed. The models are used to form a prediction and the factors are timed by systematically taking short or long positions based on this prediction. In section 7 the results are compared and discussed. Sections 8 and 9 conclude with an overview of the study's limitations as well as further research opportunities. Finally, appendices 1, 2, 3, 4 and 5 introduce detailed statistics and illustrations of the results.

2. Data and Data preprocessing

2.1. Exchange rates

The data comprise of a universe of 56 currencies, which are presented in Appendix 5, Table A5.1. The base currency is the USD. This means that the exchange rates show how much one USD is worth in another currency. Both bid and ask prices are acquired for spot, 1-month forward, 2-months forward and 3-months forward rates for a period starting from 02.01.2004 until 04.11.2022.

A forward exchange rate is a rate at which two parties agree to exchange at a given date t in the future. Forward currency rates include information about interest rates, spot prices and the time horizon. Due to the application of the interest rate parity theory (IRP), the following formula can be used to determine the rate:

$$Forward = Spot \frac{(1+i_f)^t}{(1+i_d)^t} \quad (1)$$

2. Data and Data preprocessing

where

$Forward$ = forward exchange rate

$Spot$ = spot exchange rate

i_f = the interest rate of the foreign country

i_d = the interest rate of the domestic country

t = time to expiration date

Still, one can extract those rates from real market figures. The data were obtained from a Bloomberg API. The main source of the currency time series is the Bloomberg Generic Price (BGN), an algorithm which derives bid and asks from indicative and executable quotes (Bloomberg, 2018). The data frequency used in this research is daily and represented by last prices. In other words, the ticker used for the Bloomberg API query is PX_LAST. This means that the data obtained are the last trade price. If one of the two quotes is equal zero, only the non-zero bid or ask is considered. Contrary to the equity last price, which is the last price provided by an exchange, the currencies trade a bit different. Thus, the last price in the thesis' setting can be interpreted as the last price provided for a day before 00:00 with time zone GMT +1. Additionally, missing bids were set equal to available asks and vice versa.

Figure 1 illustrates the bid for the 1-month forward USD/JPY exchange rate for the period between 02.01.2004 and 04.11.2022 as an example.



Figure 1: 1-month forward bid USD/JPY.

The data are for the period 02.01.2004 - 04.11.2022.

2.2. Real effective exchange rates

In the interest of the analysis also real effective exchange rates (REER) are gathered. The thesis uses Citi Broad Real Effective Exchange Rate Indices for 47 currencies (see Appendix 5, Table A5.1). A REER index can be used for determining whether a currency is relatively over- or

2. Data and Data preprocessing

undervalued. A high value means that the corresponding currency is losing competitiveness relative to its trading partners and may be an indication that the currency is overvalued. More precise explanation can be found in section 3.1.2. The section also discusses the economics behind the REERs as well as possible limitations of the calculation methodology. Although different index providers might have a slightly different methodology, the idea behind the real effective exchange rate is always the same. It represents a weighted sum of the real exchange rates (RER) for those currencies with which the domestic one is being most exchanged. A real exchange rate is essentially given by:

$$RER_t^{ij} = NER_t^{ij} * \frac{P_t^j}{P_t^i} \quad (2)$$

where

NER_t^{ij} = nominal exchange rate between country i and j at time t

P_t^j = price index for country j at time t

Accordingly, a REER can be as:

$$REER_t^i = \sum_{j=1}^n w_t^j RER_t^{ij} \quad (3)$$

where w_t^j is some weight, which can be derived for example from the exports and imports of country i to country j (see section 3.1.2).

Figure 2 shows the real effective exchange rate of the Japanese Yen (JPY) for the period 02.01.2004 - 04.11.2022.



Figure 2: REER Index of the JPY.

The data are for the period 02.01.2004 - 04.11.2022.

2.3. Indices

Further data on the main input variables used for prediction are gathered. This section only presents the time series. The motivation can be found in section 5. The time series indicate daily last prices for the period 02.01.2004 – 04.11.2022 of the following indices:

- **The CBOE Volatility Index (VIX):** an index calculating implied volatility from option prices on the S&P500.¹
- **Bloomberg Commodity Index (BCOM):** a broadly diversified index, derived from future contracts on commodities. Its main idea is to provide insights over commodity prices.²
- **JP Morgan G10 FX Volatility 1M Index:** a benchmark for implied volatility in G10 currencies. The index is based on 1-month option prices and constructed as a liquidity weighted average (Jankovic, Ravagli, & Sandilya, 2020).
- **TED Spread:** the difference between 3-month LIBOR and the 3-month US Treasury yield. The data were initially obtained from Bloomberg for a period 02.01.2004 – 31.01.2019. Then due to the lack of data, the following period from 01.02.2019 to 21.01.2022 was gathered from FRED. The further time series until 04.11.2022 were manually calculated using LIBOR data and the 3-month US Treasury yield.
- **Merrill Lynch Option Volatility Estimate Index (ICE BofA MOVE Index):** an index showing implied volatility derived as a weighted average of the 1-month options on US 2-year, 5-year, 10-year and 30-year US Treasuries (Kumar et al., 2017).
- **CBOE Equity Put/Call Ratio:** an index that shows the volume of traded equity put options relative to call options on S&P 500.
- **Chicago Fed National Financial Conditions Index (NFCI):** weekly time series of US financial conditions. The index is calculated as a weighted average of over 100 financial indicators.³ The index is published on Wednesdays for the week before.

3. Factor portfolios

The thesis follows a similar approach as Fama and French (1992) for isolating the currency risk factors. The idea is that the universe of valid securities is ranked based on some feature. The portfolio is then formed as a weighted average of the top/bottom n securities with the highest/lowest scores. One goes long the top n and/or short the bottom n , meaning that the

¹ More information about the methodology is to be found in Cboe Global Indices (2022). Volatility Index® Methodology: Cboe Volatility Index®

² More information about the methodology is to be found in Bloomberg (2019). Index Methodology: The Bloomberg Commodity Index Family

³ A full list of the indices is to be found from the Federal Reserve Bank of Chicago at <https://www.chicagofed.org/research/data/nfci/about>

3. Factor portfolios

portfolio returns equal the returns of the long positions minus the returns of the short positions. The portfolio is then periodically rebalanced following the same criteria.

I differentiate between portfolios based on long only positions, long and short positions and on short only positions. The top 3 and the bottom 3 currencies are taken into account. Furthermore, the research also covers three different rebalancing periods, monthly, bimonthly and quarterly. Monthly period corresponds to four weeks or 28 days. Consequently, the thesis defines the bimonthly and quarterly rebalancing frequencies as 56 and 84 days respectively.

Hoffstein, Sibears and Faber (2019) argue that similar portfolios may have a significant difference in their overall performance due to the different dates of their rebalancing. In order to overcome such constraints, I go beyond a singular portfolio approach for the various factors, holding periods and long/short exposure combinations and instead constructs multiple time series. Given a monthly holding period, this results in 20 different portfolios for every of the three long/short combinations of the factor. For bimonthly rebalancing, there are 40 portfolios. For a quarterly holding period, the thesis is able to isolate 60 different portfolios.

The variables used to rank the currencies have been adjusted before every single ranking. If a currency spot or forward exchange rate doesn't have a valid value at time t , the currency is removed from the universe of variables at time t and consequently from the ranking at time t . This step is done to reduce the number of invalid returns. Should there be an invalid return (NAs) for any other reason or due to lack of enough currencies in the universe, it is dropped.

The thesis uses the following methodology to form the factors:

1. For every day t , take the ranking variable and remove the currencies that have invalid values either for $Spot_t$ or for the n -month $Forward_t$ rate.
2. Use the new universe of the ranking variables⁴ to sort the universe of currencies.
3. Build the return for the period as follows:
 - i. For long only portfolios: as equally weighted sum of the returns of the top 3 ranked currencies.
 - ii. For long-short portfolios: as equally weighted sum of the returns of the top 3 ranked currencies minus the equally weighted sum of the returns of the bottom 3 ranked currencies.

⁴ Ranking variable is the variable used to rank the currencies. For the carry factor it is the implied yield. For the value factors it is the REER. For Momentum it is the past 1-,3- or 12-month return in USD terms (see section 3)

- iii. For short only portfolios: as equally weighted sum of the returns of the bottom 3 ranked currencies multiplied by -1.

The return of a currency is given by:

$$r_t = \frac{Forward\ Bid_{n,t} - Spot\ Ask_{t+28*n}}{Spot\ Ask_{t+28*n}} \quad (4)$$

where n is rebalancing period (either 1,2 or 3).

In other words, the return at day t presents the return between t and $t+28n$.

3.1. Value factor

The intuition behind the value factor is simple: overvalued securities tend to underperform undervalued securities. Fama and French (1992) build their research on Stattman (1980) and Chan, Hamao and Lakonishok (1991) and show that the relation between companies book and market value tend to have some explanatory power over the average US equity returns from the period 1963-1990. A company with a high book to market value can be interpreted as a value company. Respectively, a company with low book to market value is viewed as a growth company. Fama and French (1992) use book-to-market ratios to sort stocks and group them into averagely weighted portfolios. Then they build an average of the portfolios and are able to represent the factor value returns in this way.

Houweling and Zundert (2017) research factor investing within the corporate bonds markets. They calculate value factor based on credit spread using similar methodology like Fama and French (1992). Asness, Moskowitz, and Pedersen (2013) measure value in different settings and asset classes. They construct the factor in commodity markets using the log of the spot price 5 years ago divided by the current spot price. In fixed income markets, they isolate the value risk with the help of the 5-year change of the yields of a 10-year bond.

Hence, due to the different essence among asset classes and markets, there is no unique quantitative criterion for isolating value risk. The intuition though remains the same – one gets an exposure to value risk if one prefers undervalued securities over overvalued securities.

The following notions present different ways for categorizing a currency as over- or undervalued. Fortunately, there is a lot of economic research trying to explain what determines exchange rates. Consequently, academics have tried to model an equilibrium, which can be used to provide insights of where an exchange rate should be. Therefore, by observing deviations from this theoretical equilibrium one can determine how over- or undervalued a

currency is relative to another. The thesis discusses some of the most insightful concepts from the literature.

3.1.1. Purchasing Power Parity (PPP)

Asness, Moskowitz and Pedersen (2013) research the value factor also in currencies markets. The measure used is Purchasing Power Parity (PPP). Purchasing Power Parity is a concept which builds on the Law of One Price⁵ and argues that currencies have a long term equilibrium. In this equilibrium, same goods have same prices. A working paper from the Organization for Economic Cooperation and Development suggests that “PPPs appear in international trade theory in the context of equilibrium exchange rates where they are defined as the underlying rates of exchange to which actual exchange rates will converge in the long term” (OECD, 2012, p. 16). PPP Ratios therefore compare prices in different countries. “PPPs are nothing more than price relatives that show the ratio of the prices in national currencies of the same good or service in different countries” (OECD, 2012, p. 13).

The most common approach to calculate PPPs is to take a basket of goods and services for different categories and to build an average of the prices for the category. Then the categories are aggregated and an average is formed. In this way, prices in different countries are calculated and then compared (OECD, 2012).

Due to the Law of One Price, prices of same goods and services should converge to each other. A high PPP ratio signals less purchasing power of a currency. Respectively, one can evaluate which currency is under- or overvalued.

One major drawback of this approach is that goods and services, although similar, are essentially not the same. The main argument for this methodology comes from a perfect markets setting and consequently hardly considers quality or supply chains or domestic demand or other macro- and microeconomic limitations influencing goods prices. There is one easy way to overcome this shortcoming without much calculations needed. Giving up the wide diversified basket of goods and services one can compare the prices of only one product from only one company. Here the good is standardized. Furthermore, the economic limitations and barriers are reduced to the frame of only one global company. This idea can be best illustrated with the Big Mac Index. This index compares the prices of one ubiquitous product in different countries, the Big Mac. This approach, of course, has its own limitations and imperfections.

⁵ The Law of One Price states that under perfect market conditions same goods and services must have the same price. Otherwise arbitrage opportunities are possible.

There is plenty of literature discussing whether or not the PPP is relevant only from a theoretical perspective or has some application for the real market dynamics. Rogoff (1996) writes that the convergence to long term exchange rates as suggested by PPP is very slow and short term deviations are huge and very volatile. Abuaf and Jorion (1990) also confirm huge short term deviations of exchange rates from a theoretical exchange rate build on the Purchasing Power Parity approach. Nevertheless, those variations “appear to take about three years to be reduced in half” (Abuaf & Jorion, 1990, p. 1).

PPP ratios do not directly include supply and demand forces and are mainly trying to explain long term dynamics only. Furthermore, the theory states that the ultimate equilibrium of exchange rates is constant over time and thus, the exchange rates can be viewed as stationary processes.

3.1.2. Real Effective Exchange Rate (REER)

Another way to measure the value risk factor in currencies is the real effective exchange rate (REER). As noted in section 2.2, the REER of a currency is a weighted average of the real exchange rates (RER) of the currency and the currencies it is being most traded for.

There are several ways to construct a REER for there are several ways to outline the importance of foreign currencies relative to a domestic one. The first component of the index, the weights, as Ellis (2001) suggests, can be based on trade figures. In other words, the REER index is trade-weighted. “The weights are derived as the share of total trade (exports plus imports) with each country, as measured in balance of payments statistics” (Ellis, 2001, p. 15). Another way to construct the weights is to use the countries share of world trade. The third alternative approach is not to focus on trade but on productivity instead and to use countries share of world GDP.

Similarly to PPP, a vital component influencing a REER is the price basket. The data used in measuring the prices of goods and services in corresponding countries were the CPI. An improvement can be core CPI data, which do not take into account goods and services from volatile sectors like energy. Another advantage is the presence of this standardized approach for a variety of countries.

Ellis (2001) discusses major drawbacks of the REER. The research outlines potential reasons for misleading indices stemming from the methodologies and concepts used to calculate the index. Ellis (2001) stresses out that the weights used in calculating the REER are often fixed. Although easy to calculate, the approach fails to resemble most recent macroeconomic forces and limits the index proximity to real market dynamics. This drawback is overcome if the

weights are updated on a regular basis. Even then, the macroeconomic data are not provided on daily frequencies and is backward-looking. This raises the question how good short term shocks are represented in the weights. While acknowledging the validity of the critique, it is important to note that the real exchange rates (RER) do capture the immediate shocks to some extent. Further consideration is that when building weights based on trade data, those weights directly depend on exchange rate movements. This stems from the fact that the trade figures depend on local and foreign prices. Thus, import-weighted indices will behave differently from export-weighted indices. Further possible hazards of the REER's calculation methodology arise from the baskets of products and services, used to measure prices as well as the way the averaging is done and the frequency of corresponding data.

Regardless of the way the index is constructed, it combines the simplicity and powerful insights of the theory behind PPP with the real market dynamics between countries and currencies. Furthermore, the REER also involves the insight of other models, which include macroeconomic forces to explain exchange rates. The weights of the REER ultimately depend on other macroeconomic factors like education levels, productivity, capital flows etc. for these variables being the main drivers of trade between countries. In addition, given that REER is built on nominal exchange rates, it is possible to obtain daily data, which is in the interest of this research.

3.1.3. Alternative approaches for isolating the value factor

The following sections provide a concise overview of other concepts for an equilibrium exchange rate, which have gained prominence in the literature.

3.1.3.1. Behavioral Equilibrium Exchange Rate (BEER)

Menkhoff et al. (2017) show that accounting additionally for macro dynamics in the RER setting may increase the predictive power of future currency returns dramatically and thus improves the performance of value strategies. They include GDP per capita as a measure of productivity, quality of exports, net foreign assets, and output gaps. A similar approach, the so-called behavioral equilibrium exchange rate (BEER) combines macroeconomics and real exchange rates (Clark & MacDonald, 1999). BEER is essentially defined as a linear equation using some economic variables, which tries to explain the RER between two currencies. If the RER deviates from the BEER, it is expected that it should converge back to it. Consequently, measuring the deviation one can see which currency is over- or undervalued.

3. Factor portfolios

In order to isolate the value factor in currency markets Baku et al. (2020) build BEER with the help of GDP per capita, Debt-to-GDP ratios, ratio of export prices to import prices and the sum of imports and exports. Zorzi et al. (2020) point out that there are no universal variables used to construct the model. According to the paper the most important predictors of long term equilibrium real exchange rates are GDP per capita, net foreign assets and terms of trade. Thus, the authors use the following formula to estimate BEER:

$$BEER_{it} = \mu_i + \beta_1 GDP_{it} + \beta_2 NFA_{it} + \beta_3 TOT_{it} \quad (5)$$

where

GDP_{it} = gross domestic product of country i at time t
 NFA_{it} = net foreign assets of country i at time t
 TOT_{it} = terms of trade of country i at time t

BEER is shown to possess some predictive power, but it is not compulsory superior than a simple PPP approach (Zorzi et al., 2020).

3.1.3.2. Natural Real Exchange Rate (NATREX)

Another method attempting to explain an equilibrium in real exchange rates is the natural real exchange rate (NATREX). Stein (1995) defines the NATREX as the rate which makes the difference between investments and savings of a country equal to the current account in the country. This approach is similar to the ideas of macroeconomic balance and fundamental equilibrium exchange rates (FEERs). However, the NATREX extends these insights with the theory “that the real interest rate differential will be such that investors are indifferent between domestic and foreign assets” (Stein, 1995, p. 9). In other words, the expected returns between domestic and foreign assets must be the same. In the model of Stein (1995) the NATREX depends on capital, foreign debt and exogenous variables. Stein (1995) uses productivity of capital and time preference to account for the exogenous variables. Time preference is measured by Social Consumption/GDP ratio and shows how much is consumed rather than saved in an economy.

Baku et al. (2020) suggest that the natural equilibrium exchange rate is also a long term concept and fails to explain exchange rate dynamics in the short run. They also refer to Stein and Allen (1997) and point out that the explanatory variables may vary depending on the size of the economies the rate is calculated for. In this regard You and Sarantis (2012) show that for the Chinese economy the NATREX model provides better results when enriched with further macroeconomic variables.

3.1.3.3. Macroeconomic Balance (MB)

The literature examines a further approach known as the macroeconomic balance (MB). The concept models an equilibrium between two currencies as the rate which rules out both internal and external imbalances. Accordingly, this is “the rate at which the current account stabilizes at the target level, if output gaps at home and abroad are closed” (Zorzi et al., 2020, p. 7). Zorzi et al. (2020) also describe the model as:

$$MB = RER - \frac{ca - ca^{norm}}{\eta} \quad (6)$$

where ca is a projection of the current account if there are no output gaps and current exchange rates remain unchanged and ca^{norm} is the target level of current account. η describes how RER would change if the current account changes.

Although there are papers on how to specify the different components of equation (6), there is still a large room for speculation on how to determine those variables. Despite having a reasonable logic, MB does not deliver good results when forecasting real world data. Zorzi et al. (2020) prove that by examining the model for the G10 economies. Furthermore, they argue that MB delivers very volatile predictions. When testing out-of-sample, the model is the most inaccurate in predicting future exchange rates compared to BEER and PPP “irrespective of the modeler’s exact specification” (Zorzi et al., 2020, p. 19).

3.1.4. Ranking variable and factor returns

The value risk factor in this thesis is solely built on REER. It does not include a comparison between value factor portfolios formed by different models. Such an approach in a similar setting can be found in Baku et al. (2020). The authors form currency value factors using PPP, BEER and NATREX methods and conclude that PPP and BEERs are highly correlated (Baku, et al., 2020). Time series built on NATREX show essential differences compared to PPP and BEER (Baku, et al., 2020). While BEER and PPP have high (0.90 and 0.71 respectively) Sharpe ratios in G25 currencies, the authors experience lower (0.3 and 0.23) Sharpe ratios for G10 countries. The NATREX value factor has a high Sharpe ratio, up to 0.80 also for G10 currencies.

I aim at profiting from using REER not only from this methodology’s key insights as mentioned in section 3.1.2, but also by incorporating a large universe of currencies. Constructing other factors involves many layers of macroeconomic data, the presence of which is questionable for some economies. There is no exact rule how much data is needed for a machine learning model to provide reasonable outputs. However, the daily data series of the 47 REER made it possible

3. Factor portfolios

to construct monthly returns for each day. Furthermore, to minimize drawbacks arising from different styles of calculating the indices and make them comparable to one another, I only use one data provider to obtain REER.

Figure 3 illustrates the most bought and shorted currencies, which build the value factor. The top currencies for both categories are emerging market (EM) currencies. A significant percentage on the short site involves also developed market (DM) currencies.

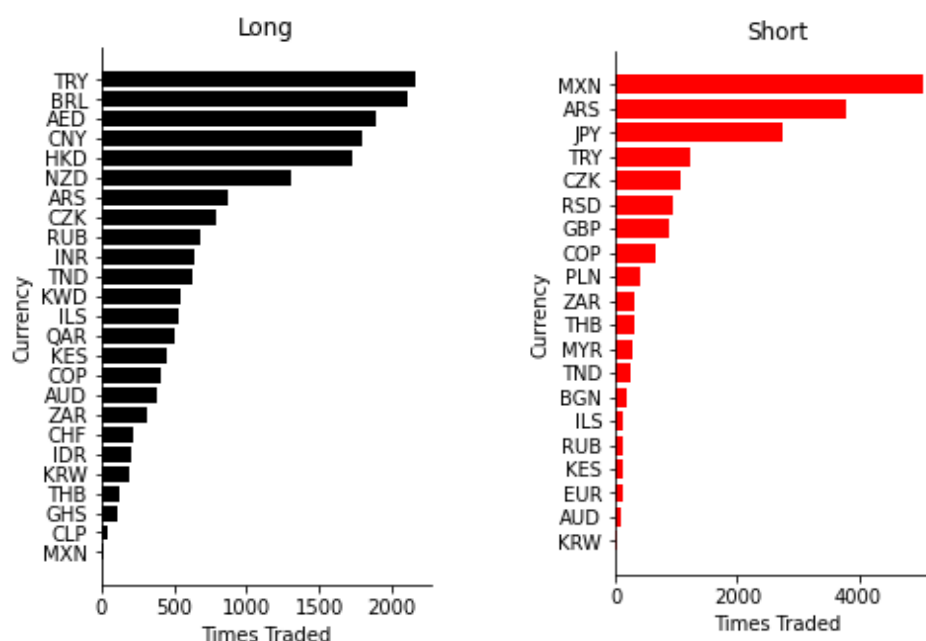


Figure 3: Most traded value factor currencies.
The data are for the period 02.01.2004 - 04.11.2022.

Figure 4 illustrates time series and distributions related to the currency value factor. Panel A presents the distribution of the factor returns based on a monthly holding period. It also distinguishes between the three distinct long/short exposures employed in the construction of the factor. All distributions are derived from monthly returns. As described in section 3, the development of the factor over time is captured by a minimum of 20 different portfolios. This approach provides a more nuanced assessment of the robustness of the factor, reducing the limitations of counting solely on end of month data and directly addressing the issue of “luck” in rebalancing, as discussed by Hoffstein, Sibears and Faber (2019). Panels B and C present the factor for bimonthly and quarterly rebalancing periods respectively.

Table 1 shows a set of numerical statistics in regard to the factor returns. The results suggest that the factor constructed with both long and short positions exhibits superior performance compared to the other two structural configurations. Notably, there is a difference between the

3. Factor portfolios

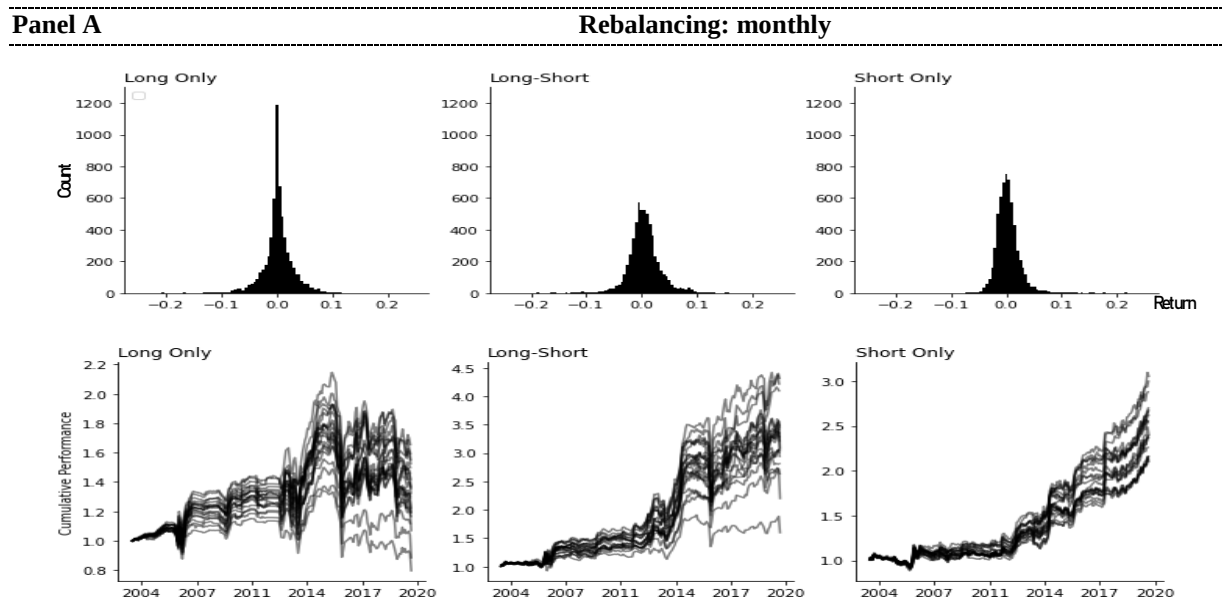
negative skewness of the long-only factor returns and the positive skewness of short only portfolios. Additionally, short only portfolios experience less variation in comparison to long only factor portfolios.

		Rebalancing		
		monthly	bimonthly	quarterly
Long Only	Mean	0,16%	0,24%	0,24%
	St.Dev	2,9%	2,1%	1,7%
	Skew	-0,97	-0,84	-0,61
	Kurtosis	7,7	4,5	3,4
Long Short	Mean	0,63%	0,64%	0,65%
	St.Dev	3,2%	2,3%	1,9%
	Skew	-0,51	0,08	0,33
	Kurtosis	6,3	3,7	1,9
Short Only	Mean	0,47%	0,40%	0,38%
	St.Dev	2,3%	1,8%	1,5%
	Skew	2	1,9	1,71
	Kurtosis	12	7,9	4,9

Table 1: Value factor monthly statistics.

The data are for the period 02.01.2004 - 04.11.2022.

The analysis reveals that the different holding periods have similar monthly dynamics. However, a higher frequency of rebalancing seems to be associated with greater kurtosis and thus fatter tails. Furthermore, the standard deviation of the factor returns increases as the holding period decreases. This suggests the presence of extreme returns within the shorter rebalancing intervals.



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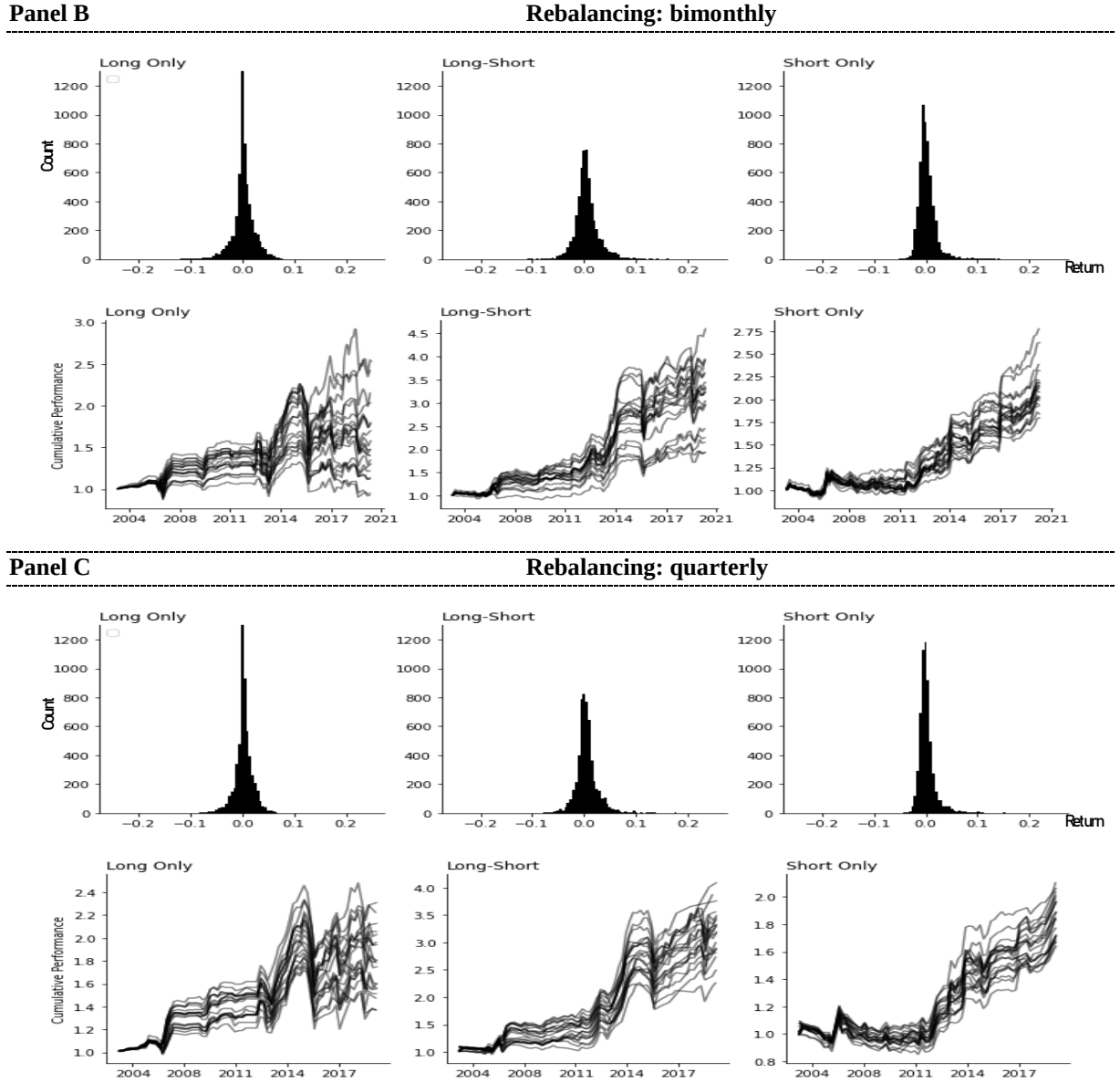


Figure 4: Value factor distributions and time-series of monthly returns.

Panel A refers to portfolios with monthly rebalancing. Panel B and C refer to portfolios with bimonthly and quarterly rebalancing respectively. The observations are for the period 02.01.2004 - 04.11.2022.

The ratio between the historical mean and standard deviation for the factor across all configurations stays between 0.05 and 0.35. This is similar to the Sharpe ratios reported by Baku et al. (2020) for G10 countries, but surprisingly far from the results for G25 currencies.

3.2. Carry factor

The literature and practitioners have long discovered an interesting phenomenon in the currency markets, which has been proven to lead to profitable trading opportunities. The occurrence is

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known as carry and it exists because of a mismatch between theoretical concepts and real life market dynamics.

At the core of the concept is the interest rate parity theory (IRP). It argues that the future exchange rate of a currency (in other words, the forward currency rate) is a function of the spot exchange rate today and the corresponding interest rates of the currencies, see equation (1). The most important argument of the IRP is the no-arbitrage logic. This means that today one can only agree to exchange the currencies at some date in the future only on the forward exchange rate given by formula (1). If this is not the case, there is an arbitrage.

A currency with higher interest rate would depreciate in the future relative to a currency with lower interest rate. However, studies have shown that in the reality the currency with the higher interest rate often appreciates relative to the currency with the lower interest rate. Fama (1984) reasons that high interest rate currencies tend to actually appreciate in the short term. In addition, he also outlines that the forward rates have a low explanatory power in predicting the future spot exchange rates movements. In other words, due to the fact that the currencies exchange rates are a direct outcome of the laws of supply and demand, the spot rates in the future often diverge from the forward rates. This opens opportunities for profit. The risks are that the exchange rate in the future might move in the opposite direction of what one has bet on. To this explicit risk and reward tradeoff I refer to as the currency carry risk premia.

The carry risk factor is captured by the strategy where one essentially systematically sells a low interest rate currency and buys high interest rate currency. This has led to positive average returns (Brunnermeier, Nagel, & Pedersen, 2008) and can be realized in practice (also) with forward contracts (Burnside, Eichenbaum, & Rebelo, 2011).

There is an extensive research on both, the performance and structure of the factor as well as on the drivers behind its returns. Burnside, Eichenbaum and Rebelo (2011) study the carry factor within a universe of 20 currencies between 1976 and 2010. They build an average weighted portfolio and observe an average return of 4.6% p.a with a Sharpe ratio of 0,86. They further compare the average weighted portfolio to a single currency portfolios and conclude that the diversified portfolio has an around two times higher Sharpe ratio (Burnside, Eichenbaum, & Rebelo, 2011). Baku et al. (2020) report a significant difference in the performance of the carry trade between G10 and EM currencies. The Sharpe ratio of EM currencies found is 1,23 for the period 2000 to 2018 compared to a Sharpe ratio of 0.4 for G10 currencies (Baku et al., 2020).

The wide literature on the FX carry phenomenon categorizes the strategy as a peso problem. In other words, there are significant infrequent losses, accompanied by regular but low positive returns (Burnside, et al., 2011). Brunnermeier, Nagel and Pedersen (2008) argue that fundamentals are unable to predict rapid and huge movements in exchange rates and focus their attention to speculators, who unwind their positions in the FX markets. Consequently, the authors reason that general uncertainty and high volatility expectation in the markets reduce speculator positions and thus limit the negative impact on carry trade returns. A “higher level of VIX predicts higher returns for investment currencies and lower returns for funding currencies” (Brunnermeier, Nagel, & Pedersen, 2008, p. 314). A significant argument put forth by Brunnermeier, Nagel and Pedersen (2008) is that when investors face financial constraints, they tend to liquidate their FX positions. This phenomenon assumes a crucial role in shaping exchange rates dynamics and underscores the importance of liquidity risk as a driver of this currency risk premia. Similarly, Egbers and Swinkels (2015) investigate the relation between volatility and the currency carry factor. They make an attempt to time the factor using the VIX and VXY⁶ but conclude that the excess returns are statistically non-significant. Also focusing on FX volatility Menkhoff et al. (2012a) found a negative correlation between high interest rate currencies returns and high unexpected volatility on the FX market.

3.2.1. Ranking variable and factor returns

I build the carry factor by ranking currencies on implied yields. The implied yield is essentially an expected return given that exchange rates do not change. It is given by:

$$\text{Implied Yield}_t = \frac{\text{Forward}_t}{\text{Spot}_t} - 1 \quad (7)$$

In general, the carry portfolios go long on the three currencies with the highest implied yields and/or short on the three currencies with the lowest implied yields. Due to equation (4) this approach precisely captures the basic insights of the aforementioned strategy.

Figure 5 shows the most traded currencies for the carry factor for the period 02.01.2004 - 04.11.2022. Overall, the long exposure consists of EM currencies while the short exposure involves currencies from developed economies like Japan, Great Britain and Switzerland. A few interesting exceptions are the Botswana Pule as well as the Uganda Schilling which seem to be among the top shorted currencies.

⁶ VXY is an index, which measures the volatility of the G7 currencies.

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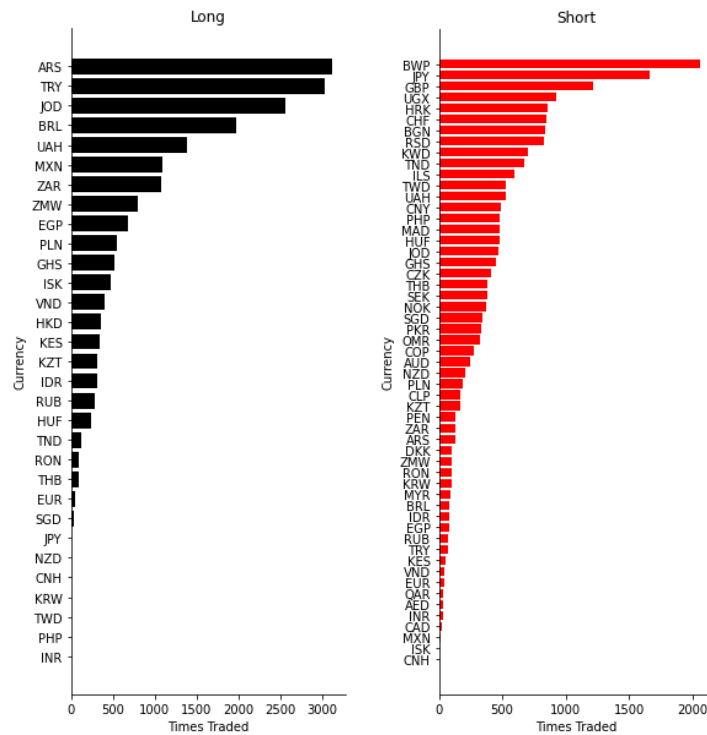


Figure 5: Most traded carry factor currencies.
The data are for the period 02.01.2004 - 04.11.2022.

Indeed, the forward rates of those currencies are often lower compared to the spot prices, despite that the countries have high interest rates for the given period. This implies potential market inefficiencies and is further discussed as a limitation in section 8.

		Rebalancing		
		monthly	bimonthly	quarterly
Long Only	Mean	2%	1,8%	0,47%
	St.Dev	3,4%	6,4%	2,6%
	Skew	-1,39	-30,4	-7,9
	Kurtosis	7,9	12,75	224,3
Long Short	Mean	2,9%	2,5%	1%
	St.Dev	4%	6,6%	2,7%
	Skew	0,4	-28,2	-6,4
	Kurtosis	9,3	11,58	198,2
Short Only	Mean	1,1%	0,7%	0,54%
	St.Dev	2,7%	1,8%	1,6%
	Skew	3	2,4	2,8
	Kurtosis	35,1	16,6	20,2

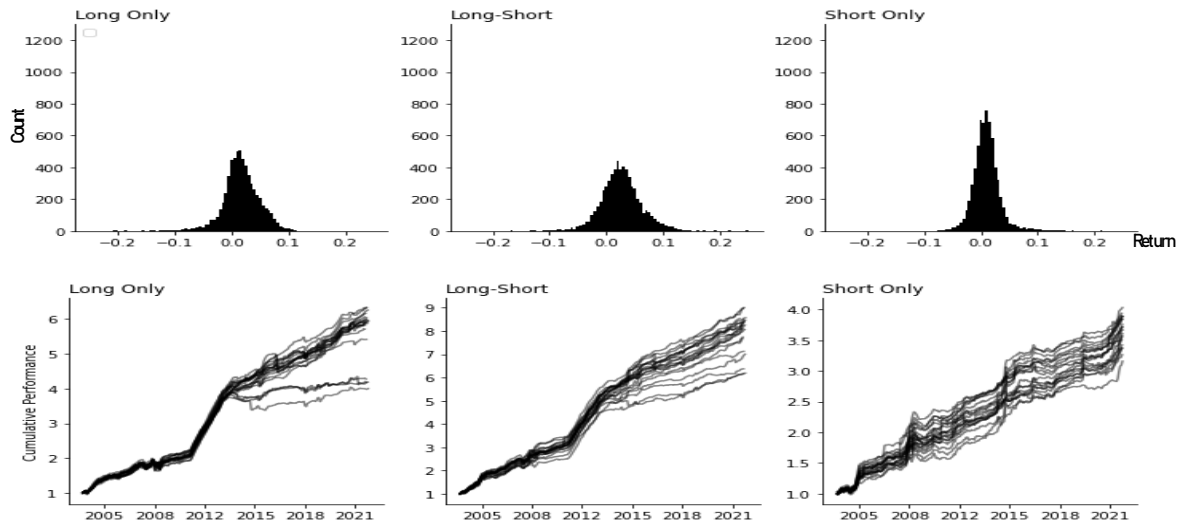
Table 2: Carry factor monthly statistics.
The data are for the period 02.01.2004 - 04.11.2022.

3. Factor portfolios

Table 2 provides summary statistics of the carry factor. The monthly returns of the factor are between 1%-2% on average. The monthly rebalancing period seems to possess the highest average return. The factor returns with quarterly holding period experience the lowest volatility. The higher rebalancing frequency is associated with higher risks of crashes. Besides, a negative skewness is observed for long only and long/short combinations of the factor.

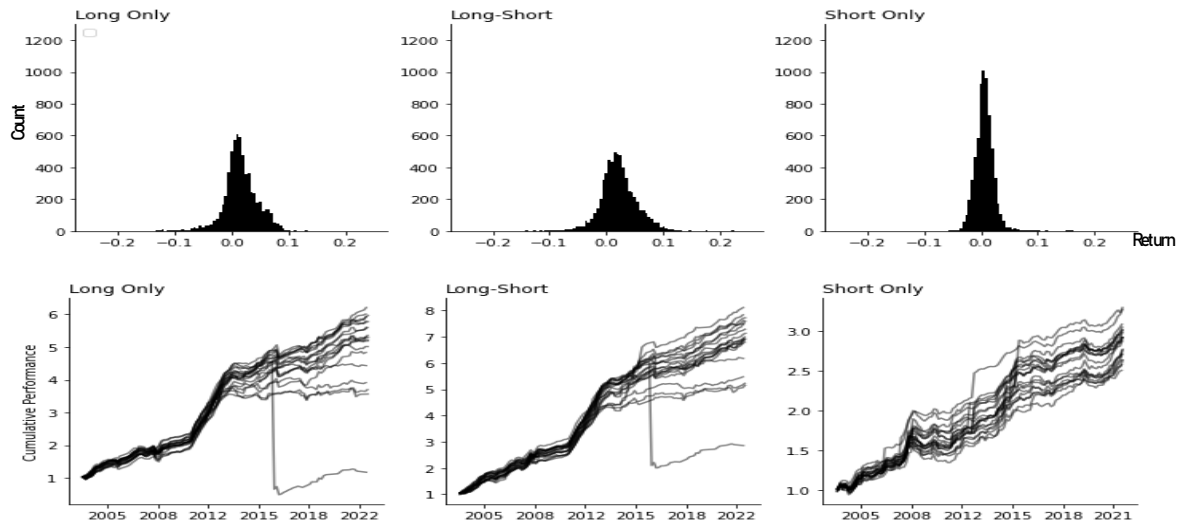
Panel A

Rebalancing: monthly



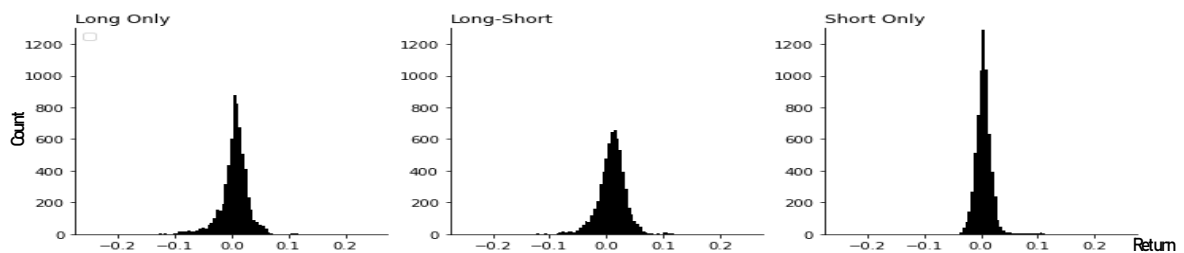
Panel B

Rebalancing: bimonthly



Panel C

Rebalancing: quarterly



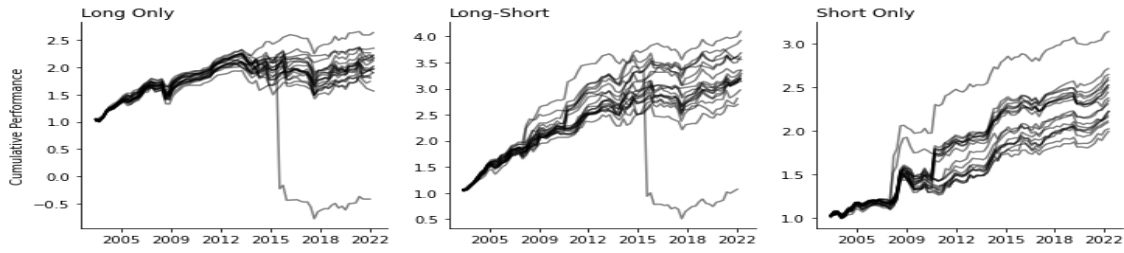


Figure 6: Carry factor distributions and time-series.

Panel A refers to portfolios with monthly rebalancing. Panel B and C refer to portfolios with bimonthly and quarterly rebalancing respectively. The observations are for the period 02.01.2004 - 04.11.2022.

The long/short structure of the factor appears to perform best. By comparing the mean to standard deviation ratios to Sharpe ratios of the carry factor from the literature, one can conclude that they are very similar, especially for portfolios with more frequent rebalancing periods. Examples to such studies are Baku et al. (2020) and Brunnermeier, Nagel and Pedersen (2008).

Further visualization of the factor can be found in Figure 6, which depicts the distributions as well as time series of the factor. The illustration also captures the tail risks of the carry factor. This corresponds to the peso problem narrative described in the literature.

3.3. Momentum factor

The momentum factor is a very wide and thoroughly documented phenomenon in all financial markets. Some of the most prominent examples of such literature are Rouwenhorst (1998), Fama and French (2018) and Asness, Moskowitz and Pedersen (2013). The simple method of buying assets with positive past performance and/or selling assets with negative past performance seems to have been a robust profitable investment strategy among asset classes and time. Fama and French (2018) even include the factor in their six-factor asset pricing model approach. They isolate momentum on the US equity market by ranking the stocks based on their performance from the past period between $t-12$ to $t-2$ (Fama & French, 2018).

The presence of the momentum factor is also documented for other stock markets and among different industries. Rouwenhorst (1998) shows that several stock markets face medium-term continuation of past returns and is able to structure momentum portfolios with significantly positive performance. The studied markets are Austria, Belgium, Germany, Spain, Sweden, Italy, France, Denmark, the Netherlands, Norway, Switzerland, and the UK. All experience strong correlation with the momentum phenomena from the US equity market (Rouwenhorst,

3. Factor portfolios

1998, p. 267). Moskowitz and Grinblatt (1999) investigate how industries can explain momentum in US stock market. They found out that the industry accounts for a huge part of the performance of the factor. Consequently, the authors are able to form a profitable investment strategy based on industry momentum.

Asness, Moskowitz and Pedersen (2013) conduct a thorough study of the momentum phenomenon with regard to currencies, commodities, fixed income and equity. Their research stretches to G10 currencies denominated in USD. The summary statistics of the currency momentum factor for the period from 1979 to 2011 indicate a mean of around 3% on a monthly basis with a standard deviation of 9,6%. Menkhoff et al. (2012b) also investigate the momentum factor in currency markets and observe that the excess returns differ by of 10% p.a between the returns of past winners and past losers.

Now that the momentum factor is present in the markets, the several studies try to highlight the reasons for its profitability. One of the popular opinions on the topic is that the factor can be explained by investors cognitive biases and irrationality. Chui, Titman and Wei (2010) study how different cultures impact momentum returns. They use the model of Hofstede (2001)⁷. The findings suggest that the variable individualism has a strong connection to momentum returns as well as trading volume and volatility. They also show that momentum “profits are also positively related to analyst forecast dispersion ... and negatively related to firm size and volatility” (Chui, Titman, & Wei, 2010, p 361). Jegadeesh and Titman (1993) indicate that the returns may be due to delayed information digestion and reaction. De Bondt and Thaler (1987) find a profitable investment approach, which also is solely based on past performance. The behaviorists conclude that the behavioral bias of overreaction manages to explain the strategy returns.

Further explanations behind the momentum factor evolve to market imperfections like information asymmetry and transaction costs. Chui, Titman and Wei (2010) conclude that momentum returns depend on “transaction costs and the familiarity of the market to foreigners” (p. 361).

Credit risk is also thought to have some explanatory power in forecasting momentum returns. Avramov et al. (2007) build their research on 3578 companies listed in the US. They show that

⁷ The model has six dimensions, which are used to categorize countries cultural differences. The dimensions are power distance (distribution of power among a society), individualism, masculinity (a variable which characterizes whether the society is striving for cooperation and harmony or success and materialistic achievements), uncertainty avoidance, long term orientation and indulgence (Hofstede, 2001).

in the period between 1985 and 2003, when excluding companies with S&P credit rating lower than BBB, the momentum returns are statistically insignificant. The companies in the momentum portfolio tend to have low creditworthiness and subsequently high credit risk.

3.3.1. Ranking variable and factor returns

In this thesis I follow a similar approach as Menkhoff et al. (2012b). They use a data set of 48 currencies spot rates and 1-month forward rates all denominated in USD for the period from 1976 to 2010. They form portfolios, which capture the momentum by ranking the currencies based on past 1-, 3-, 6-, 9- and 12-month performance. Furthermore, their research accounts for one-, two- and three-months rebalancing period.

I also build the momentum factor on three different ranking variables, the last one, three- and twelve-month performance in USD terms. One gets a long exposure to currencies, which are appreciating relative to the USD and sells currencies, which depreciate relative to the USD. Similarly, the work also distinguishes between the three different rebalancing periods, monthly, bimonthly and quarterly. Lastly, as mentioned in section 3 I aim at capturing the factor also with different long/short position combinations. Hence, the three different methods for factor construction are also implemented for the momentum factor.

Figure 7 shows a brief summary of the currencies used in structuring the long and short positions of the momentum factor. Similarly to the carry factor but unlike to the value portfolios, the number of currencies used for this strategy is higher. The amount of different currencies bought is more than the number of currencies sold for all three momentum factors. Figure A5.1 and Figure A5.2 in Appendix 5 show the currencies used in constructing the 3m-momentum and 12m-momentum factor.

Graphic representations of the distributions as well as time-series of the momentum factor can be found in Appendix 4 Figures, A4.M1-1, A4.M3-1 and A4.M12-1. Again 20 portfolios for every holding period and long/short exposure have been obtained due to the daily data frequency to capture the performance of the factor. Tables 3 and 4 describe numerically some of the key statistics of the three different momentum factor variations. The 12m-momentum performs best in terms of average returns.

3. Factor portfolios

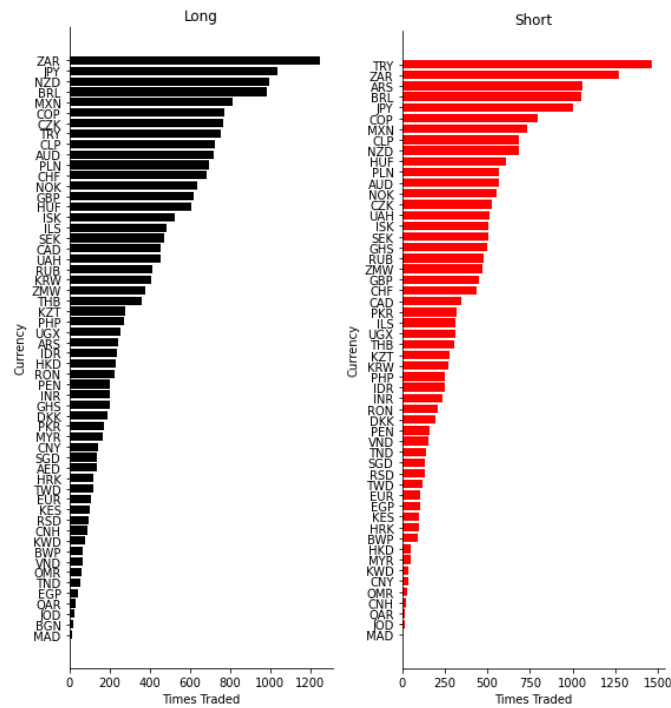


Figure 7: Most traded 1m-momentum factor currencies.
The data are for the period 02.01.2004 - 04.11.2022.

The other two variations even have a negative mean with long only and long-short positions. Baku et al. (2020) present similar results, they also conclude that the 12-m momentum best captures the strategy. Unlike Menkhoff et al. (2012b), the results do not suggest high Sharpe ratios and excess returns of up to 9% p.a. After comparing both the means and standard deviations, the short only approach seems to have the best performance. Similarly, the monthly rebalancing period appears to deliver the highest returns.

		Rebalancing		
		monthly	bimonthly	quarterly
Long Only	1m-Mom	-0,2% / (3,5%)	-0,1% / (2,7%)	-0,03% / (2,3%)
	3m-Mom	-0,2% / (3,8%)	-0,1% / (2,9%)	0,02% / (2,3%)
	12m-Mom	-0,2% / (3,9%)	0,1% / (2,9%)	0,1% / (2,7%)
Long Short	1m-Mom	-0,01% / (3,6%)	-0,04% / (2,6%)	-0,02% / (2,1%)
	3m-Mom	0,02% / (4%)	0,01% / (2,9%)	0,04% / (2,2%)
	12m-Mom	0,2% / (4%)	0,3% / (2,7%)	0,3% / (2,6%)
Short Only	1m-Mom	0,2% / (2,7%)	0,02% / (1,9%)	0,02% / (1,7%)
	3m-Mom	0,2% / (2,6%)	0,02% / (2%)	0,02% / (1,7%)
	12m-Mom	0,3% / (2,4%)	0,3% / (1,8%)	0,3% / (1,5%)

Table 3: Momentum factor mean / (standard deviation).

4. Factor timing

In Table 4 all momentum variations have positive skewness for short only portfolio constructions. The 12m-momentum has the highest kurtosis among every rebalancing frequency and portfolio construction method. This signals significant tail risks.

		Rebalancing		
		monthly	bimonthly	quarterly
Long Only	1m-Mom	-1 / (4,4)	-1,3 / (4,3)	-1,6% / (6)
	3m-Mom	-1,6 / (9,1)	-1,4 / (4,9)	-1,4 / (5)
	12m-Mom	-1,3 / (7,9)	-1,2 / (5)	-7,1 / (179,1)
Long Short	1m-Mom	-0,4 / (3,3)	-0,6 / (3,4)	-0,9 / (5,7)
	3m-Mom	-1,1 / (6,6)	-0,96 / (4,1)	-0,85 / (4,7)
	12m-Mom	-0,75 / (6,4)	-0,29 / (3,44)	-8,7 / (267,1)
Short Only	1m-Mom	0,9 / (4,7)	0,6 / (2,3)	1,7 / (9,4)
	3m-Mom	1,2 / (6,4)	1,6 / (7,9)	2,1 / (11)
	12m-Mom	2,1 / (12,8)	2,4 / (12,9)	2,6 / (14,5)

Table 4: Momentum factor skewness / (kurtosis).

4. Factor timing

After constructing the factors, I focus on the timing of the factors and present the models as well as the forecasting variables used in the process. An important consideration is that the values of the input variables, used for forecasting at day t correspond to the last prices for the variables obtained at day t . In contrast, the return of the factor at day t corresponds to the return obtained for a period starting from day t and ending after $t+28n$ days (where $n=1,2,3$ depend on the holding period), see section 3. The models are always trained with data until including $t-1$. Then the values of the variables at day t are introduced to the models. The algorithms then give the forecast at day t (1 if a non-negative return is expected and 0 if a negative return is expected), which is essentially the prediction for the factor return for n periods ahead. The factor is then timed by going long if the prediction is 1 and going short if the prediction is 0.

The general approach for all models is the same and is built on the following steps:

1. The factor portfolio returns are transformed to 1 if they are positive and 0 otherwise.
2. The data from $t-1$ to $t-1320$ are used in order to train the models and obtain optimal parameters.⁸

⁸ The intuition behind using this length of the data set is that it approximately represents five years of data.

3. The values of the input variables at t are introduced to the model. This results in a prediction of either 1 or 0.
4. Based on the prediction, the factor is then timed by going long the factor if the prediction is 1 and short the factor if the prediction is 0.

After obtaining the returns of the timed factors, an analysis is conducted to enhance the comprehension of their performance. More specifically, a minimum of 20 distinct portfolios are again derived for each factor setting.

5. Predictive variables for forecasting factor returns

As mentioned in previous chapters, there are studies discussing the determinants behind the currency factor returns. Such variables will be needed for forecasting as well as training the models.

The thesis summarizes the main drivers under four major categories and accounts for them with the indices mentioned in section 2.3. The four main categories used in timing the currency factors portfolios are macroeconomic, volatility, liquidity and capital flows.

5.1. Capital flows

Since the fall of the Bretton Woods System in the 1970s, most of the world currencies are freely floating. This means that an exchange rate forms directly by the rules of supply and demand. Thus, global trade of goods, services and financial assets has a straight impact on exchange rates and consequently influences the different currency factor portfolios dynamics. In section 3.1 some theoretical concepts, which examine equilibrium exchange rates, were presented. Main points in some of the models were variables characterizing capital flows between two economies.

I account for this dimension with the help of the REER of the currencies of the five biggest economies, USA, EU, China, India and Japan. As presented by formula (3) in section 2.2 and then discussed in section 3.1, the REERs include information about the trading volume between different countries in their weights.

5. Predictive variables for forecasting factor returns

An important consideration is the use of the REER indices for calculating the currency value factor.⁹ Despite this, the REERs showed promising results in forecasting also other factors (see Table A5.2 in Appendix 5). Additionally, the REERs are only used as a ranking variable. Thus, they are not directly present in the calculation of the value factor returns. Figure 3 suggests that the five currencies are not always ranked among the top or bottom. Therefore, the currencies are not always traded and don't always have a straight impact on the value factor returns.

To account for other economies, which may not be covered by the information in the REERs, the BCOM index is introduced. The idea is that there is a variety of smaller economies, whose added value comes primarily from extracting raw resources. From their perspective, a relative high commodity price indicates a high demand or a scarce supply of a precious resource. Therefore, the exchange rate of the currency in which the good is mostly traded should somehow react. In order to account for such economies and their trade dynamics, this commodity price index is used.

5.2. Macroeconomics

The equilibrium exchange rates models in section 3.1 also incorporate macroeconomic information. The dependencies between variables such as innovation, education, productivity, employment rates, and variables resembling investments, government balance sheets, popularity, corruption and power are complex and a subject to never-ending research. Arguably, those variables are ultimately the drivers but also the result of trade between economies. A basic macroeconomic logic leads to the expectation that under transparent and supportive government and investments in education, there will likely be an increase in innovation and productivity, which ultimately increases trade and demand for a currency.

Colombo, Forte and Rossignoli (2019) introduce the NFCI index as an attempt to forecast the carry factor returns. The index summarizes data from US financial institutions in order to suggest how favorable the financial conditions in the world's biggest economy are. Among the variables used are credit spreads, surveys data, and total assets of financial institutions to US GDP. The index includes overall more than 100 macro indices. Colombo, Forte and Rossignoli (2019) show that, when introducing to a support vector machine (SVM) the NFCI improves the Sharpe ratio of the simple carry factor.

⁹ The USD real effective exchange rate hasn't been used for the construction of the value factor because the USD is used as a base currency.

5. Predictive variables for forecasting factor returns

Brunnermeier, Nagel and Pedersen (2008) discuss the funding restrictions and the following unwinding of investors positions as a potential determinant of carry factor returns. Such ideas are also captured by the NFCI index. The presence of credit spread indices in the composition of the NFCI is connected to the insights of Avramov et al. (2007), where the momentum factor in equity markets depends on credit risk. Furthermore, the currency momentum factor is linked to transaction costs and irrational decisions from investors (Menkhoff et al, 2012b).

5.3. Volatility

Volatility, in particular the uncertainty of the equity market, has been studied as a determinant of the carry currency factor (Brunnermeier, Nagel, & Pedersen, 2008). The paper directly uses the VIX as a predictor for carry factor returns. Lustig, Roussanov and Verdelhan (2011) distinguish between high and low interest rate currencies and develop a risk-based approach on exchange rates. They identify a global risk factor and point out that it “is closely related to changes in volatility of equity markets around the world” (Lustig, Roussanov, & Verdelhan, 2011, p. 3731). The carry factor returns also have been associated with negative performance during “global flight-to-safety events” (Accominotti et al., 2019, p. 2233). The volatility on the foreign exchange markets also is considered to have an impact on currency factor returns. Menkhoff et al. (2012a) calculate a global FX volatility from a universe of 48 currencies and find significant effects between the volatility measure and currency carry factor returns.

I aim at capturing volatility dynamics using multiple indices from different markets. To account for the equity market volatility, the CBOE VIX index as well as the CBOE Equity Put/Call ratio are used. The fixed income markets volatility is obtained via the ICE BofA MOVE index. JP Morgan G10 FX Volatility 1M index accounts for the foreign exchange markets volatility

5.4. Liquidity

Engel and Wu (2018) present a complex perception on liquidity in the bond market and the high demand for government fixed income securities, which in turn influences exchange rate dynamics. They show that the spread between “riskless private bond return and government bond return” (Engel and Wu, 2018, p. 2) can explain exchange rates of G10 economies. As previously mentioned, the findings of Brunnermeier, Nagel and Pedersen (2008) also refer to liquidity risks as a potential driver of carry returns. Similarly, Mancini, Rinaldo and Wrampelmeyer (2013) suggest that liquidity significantly impacts the currency carry factor. Furthermore, the value risk factor, measured as a combination of value factors in the majority

of markets, is negatively correlated with liquidity risk. In contrast, the momentum factor, again defined as a mixture from momentum factors of different asset classes, relates positively to shrinking liquidity (Asness, Moskowitz, & Pedersen, 2013). In the setting of this thesis the TED Spread is used as a measure of liquidity risk.

6. Models

This section introduces the specifications of the models employed for timing the factors. I use a type of machine learning technique known as supervised learning. Such algorithms rely on past labeled data during the training phase and are mostly used for generating forecasts. The term labeled data denotes that the values of the predictor variables are associated with a corresponding outcome prior to the training process (Raschka & Mirjalili, 2017). The outcome variable captures the factor return, presented as either 1 or 0. In the context of supervised learning, the models are only used for classification purposes since the outcome variable is binary. This imposes that the prediction of the models also will be either one of the two classes 0 or 1. An alternative to this methodology is a regression approach. Here the outcomes in the training data as well as the predictions are considered as continuous variables (Raschka & Mirjalili, 2017). In order to ensure comparability and consistent interpretations of the results, I employ identical model parameter specifications across all factors and factor constructions.

6.1. Logistic Regression

The first model used in order to form predictions for the factor returns, expressed as a binary variable, is the logistic regression. The model uses a sigmoid function to transform inputs in values between 0 and 1. An output value of less than or equal 0.5 is converted to 0 and viewed as a non-positive return prediction. Output values higher than 0.5 are converted to 1, accounting for a positive return prediction. The optimization algorithm used in the process is the maximum likelihood.

6.2. K-Nearest Neighbors (KNN)

The K-Nearest Neighbors is a supervised model used mainly for classification tasks. The algorithm filters all training set data points, which are within a certain range to the parameters of the variable to classify. Observing only those “neighbors,” the model then returns the class

6. Models

with the highest occurrence. The KNN is the simplest method among the supervised classification models and also requires less time and computational power.

The specifications of the algorithm used in the thesis are:

- **N: 9**
Explanation: number of neighbors
- **Metric: Minkowski**
Explanation: a specification on how the distance between the variable to classify and the training data points is measured
- **P: 2**
Explanation: P is a further specification on how the Minkowski distance should be calculated. I use the Euclidean distance between two points (x_1, x_2) and (y_1, y_2) in the two dimensional space which is given as

$$\sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

Prior to the specification of the parameters, preliminary tests were carried out to assess the model performance.

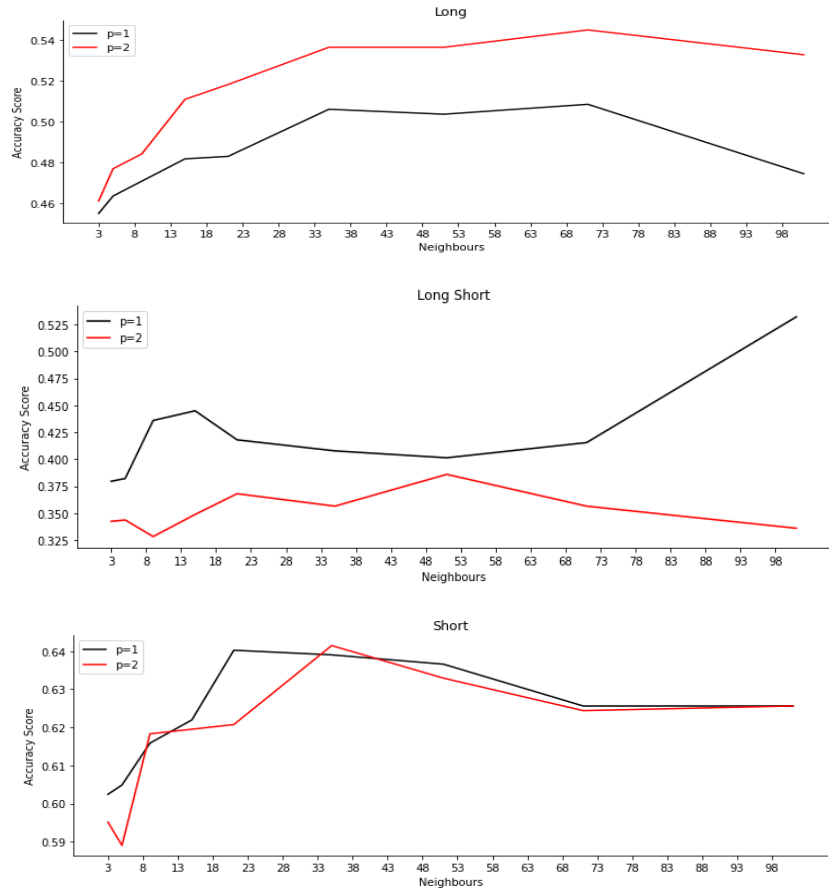


Figure 8: Accuracy score of KNN for different p and n specifications.

The results are for value factor with monthly holding period. The accuracy depicted refers to the accuracy tested on 20% from the total data dataset.

The entire available data were divided into two subsets, with the first 80% data points as training data and the rest 20% test data. A KNN model was then trained using the training dataset. This enabled the generation of forecasts based on the variables from the test dataset. Then the relation between the correctly predicted outcomes and the actual outcomes from the test dataset was evaluated. This ratio is known as accuracy score. Figure 8 illustrates an example of the accuracy scores obtained for a different number of neighbors as well as different specifications of the distance metric. No clear pattern among rebalancing frequencies and long/short exposure was present for all factors. However, the most significant improvement of the accuracy scores happened for a number of 9 neighbors. There was no clear difference in the performance of the diverse p specifications. I chose to use the best performing p for the long/short combination of the factors, because in the literature the risk factors are mainly build with both long and short positions (Fama and French, 1992). Thus, the KNN models were parameterized with 9 neighbors and $p=2$.

6.3. Support Vector Machines (SVM)

The Support Vector Machine is an algorithm, which if used for classification tasks aims to find an optimal separating gauge between the different outcome classes by maximizing the margin between the nearest data points and a separating hyperplane (Raschka & Mirjalili, 2017). If the data are linearly inseparable, then some misclassifications may be allowed. The algorithm also deals with linearly non-separable data by projecting the data to higher dimensions, using some function, and find the optimal linear separation. The optimization problem involves the inner product of the vectors defining the information about the data points. The so-called kernel tricks make it possible to reduce the computation power and time needed for executing the model, by avoiding unnecessary calculations. A kernel function directly specifies this inner product of the data points in the transformed space. This implies that there is no need no to either specify or compute the exact function, which projects the data to the higher dimensional space. There are many different specifications of the kernel function. The most popular are the Gaussian radial basis function, the sigmoid function, a linear function as well as a polynomial function. A more detailed explanation of the algorithm can be found in Raschka & Mirjalili (2017).

I apply the SVM model with the following parameters:

- **Kernel function: Gaussian radial basis function (RBF):**

$$K(x^i, x^j) = \exp\left(-\frac{\|x^i - x^j\|^2}{2\sigma^2}\right)$$

where x^i, x^j are the vectors, containing the features of the corresponding data points

- **Gamma: 0.1**

Explanation: γ corresponds to the curvature of the separating hyperplane for the original space. The higher the γ , the higher the influence of the training data samples (Raschka & Mirjalili, 2017). For the RBF function γ is given by:

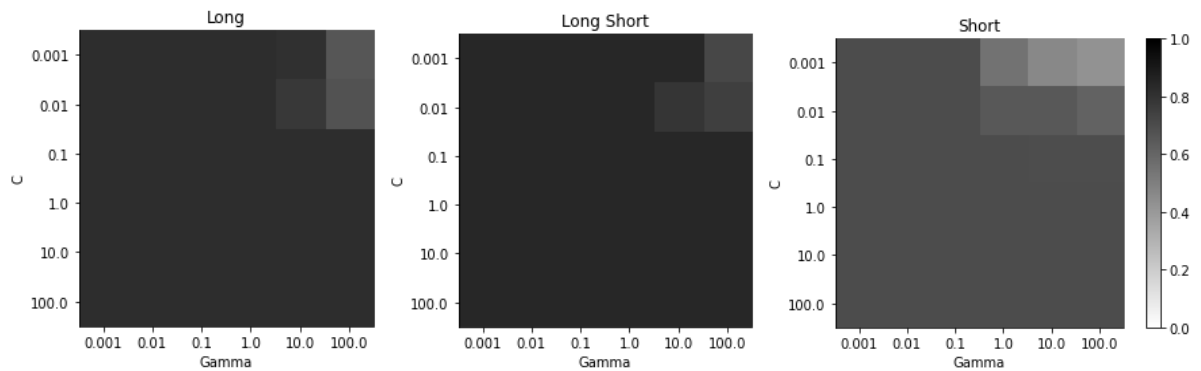
$$\gamma = \frac{1}{2\sigma^2}$$

- **C: 10**

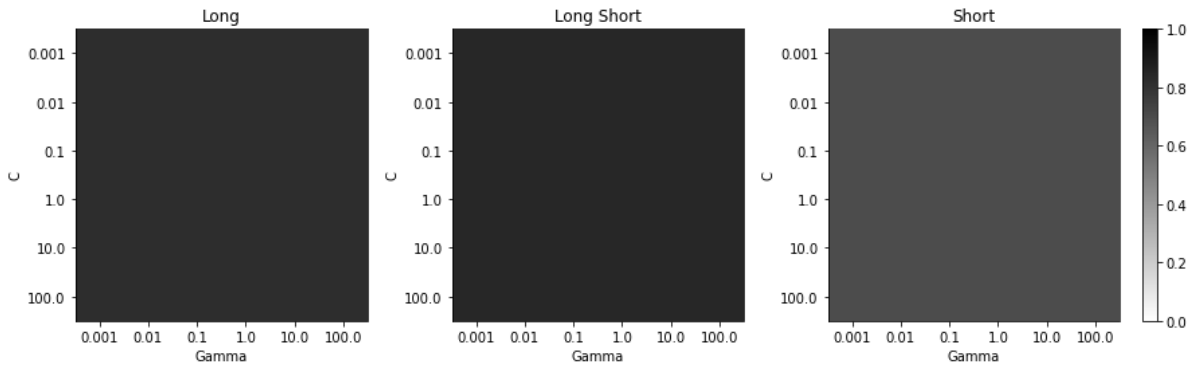
Explanation: C is a parameter controlling for allowed errors. If C is low, then less errors are allowed.

To motivate the exact specification of the model parameters, few tests were carried out. Figure 9 depicts an example, showing different accuracy scores of the model for different C values, values of γ and kernel functions. An accuracy score is defined in section 6.2. The darker an area is, the higher the accuracy score of the algorithm. The plots refer to the carry factor and present results based on monthly rebalancing and long only positioning. Similarly to the KNN models, the available data were first split into training and test data containing 80% and 20% of the data points, respectively. Those 20% of the data were used to form predictions and then ultimately test the accuracy of those predictions. There was little difference in the forecasting performance between the kernel functions for all factors and factor structures. Although on few instances the accuracy of the sigmoid predictions was slightly better than the RBF function, the RBF performed slightly better on average for all factors. This was especially true for high values of C and low values of γ . Based on the outcomes of these tests, I proceeded with the above mentioned parameter specifications.

Kernel Function: RBF



Kernel Function: Sigmoid



Kernel Function: Polynomial

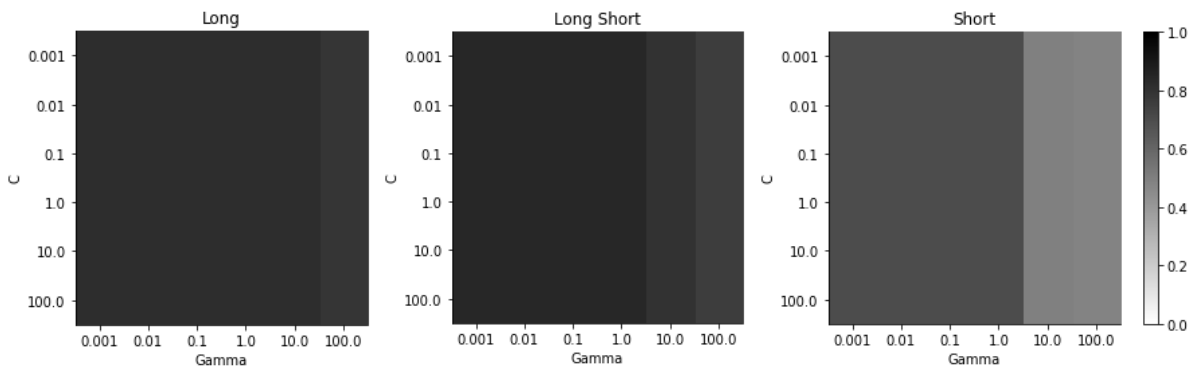


Figure 9: Accuracy scores of SVM for different gamma and C specifications. The results are based on the carry factor with monthly holding period.

6.4. Random Forests

One of the most used and easy to understand supervised machine learning algorithms for classification is the random forest (RF). The core of the mathematics behind RF builds on decision trees and probability theory. Decision trees are essentially if-else statements, which optimally divide randomized data by maximizing informational gain objectives. Different decision trees may result in different outcomes, due to the input data. The random forest comprises of a large number of decision trees and takes the most frequent outcome from the trees as the outcome of the forest.

I use the following important specifications for the model:

- **n: 100**
Explanation: n is the number of trees
- **random state: 1**
Explanation: The data, which enters into the model, firstly is randomly reshuffled. A random state of 1 ensures that the exact same shuffling sequence will be reproduced if the model is executed again. The replication of the outcomes is thus more straightforward.

- **Criterion: Gini**

Explanation: The variable defines the so-called impurity measure. The optimization objective when splitting data among the nodes of the single decision trees is to maximize the information gain. The information gain is calculated as:

$$IG = I(\text{parent}) - \frac{n_{\text{child left}}}{n_{\text{parent}}} I(\text{child left}) - \frac{n_{\text{child right}}}{n_{\text{parent}}} I(\text{child right})$$

where $I(\cdot)$ is the impurity function. An impurity function is essentially a function, which measures how pure a group of data points is. n is the number of data points in a node. The Gini impurity function is given by

$$Gini = 1 - \sum_{i=1}^2 p(i)^2$$

where $p(i)$ is the number of data points in the node from class i divided by the total number of data points in the node.

There are several possible specifications of this parameter. Examples include Gini, Entropy and Log Loss.

Figure 10 compares the average accuracy scores of the different criteria. The tests were done with a split of the available data on 80% training dataset and 20% data for testing. The accuracy is tested on the test dataset. The average of each factor is built as the average of each factor construction for each rebalancing period. The momentum factor average includes only the 12m-momentum, since it performs best among the different momentum factor specifications. The different criteria behaved very similar. I use the Gini function for the factor timing.

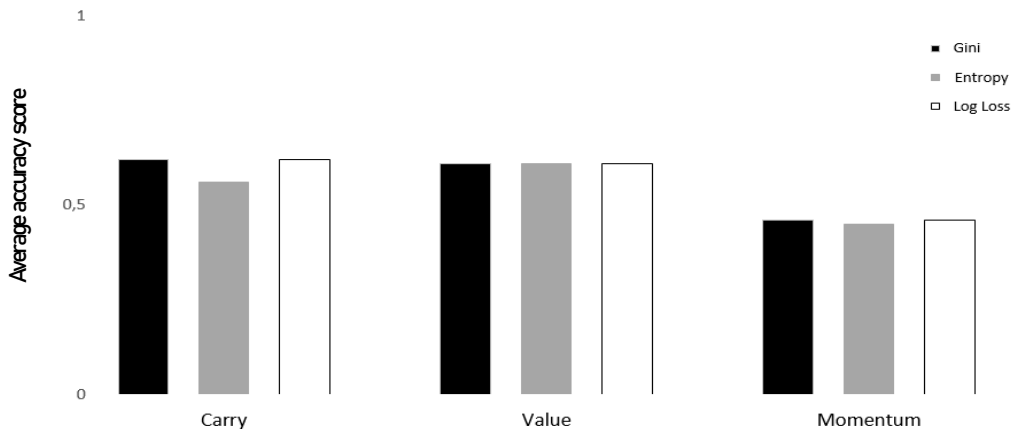


Figure 10: Average accuracy score for different impurity measures for the random forest.

6.5. Recurrent Neural Networks (RNN)

Neural networks refer to an algorithm, which is constructed from multiple neurons, organized in multiple sequentially connected layers. Figure 11 presents an example of a neural network. A neuron can be defined as a unit, which receives some input, plugs this input into a function

and produces an output. This function is often referred to as an activation function. The word activation comes from the idea that the function also determines whether the output is used as an input to further connected neurons. The neurons are organized in an input layer, hidden layers and an output layer, which are connected in a way as shown in Figure 11. The neurons in the input layer correspond to the input values to the model. Those are the twelve different variables used for forecasting the factor returns. Each connection between those values and the neurons from the hidden layer are associated with some weights and biases. A bias is nothing more than a random number. The sum of the weights, multiplied by the corresponding input values, and combined with the biases serve as an input to the neurons from the hidden layer. The activation function transforms the sum. If the output is above certain level the node is “activated” and the value is passed to the neurons of the next hidden layer, or if there are no further hidden layers to the output layer. The outputs from the hidden layer together with the corresponding weights and biases serve as an input to the activation functions of the output layer. The output of the output layer is compared with the true value associated with the input variables to the input layer. A cost function quantifies the difference between the two values. In the training phase, many neural networks use a gradient approach to measure the magnitude of the change needed so that this difference is minimized. Subsequently, a process known as backpropagation updates the weights and biases between every node and layer using the information from the cost function and the gradient. Once the weights are adjusted the same steps are repeated multiple times until the computer converges to an optimal solution for the cost function and obtains the weights and biases leading to this solution. The process is known as gradient descent.

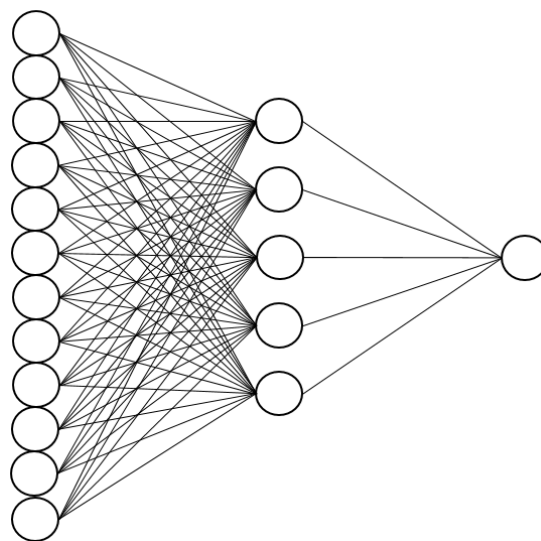


Figure 11: *RNN layers visualization.*

6. Models

Recurrent Neural Networks are a type of neural networks used for sequential data. Similarly, there are weights, biases, activation and cost functions. The main difference to the neural networks described above lies in the fact that RNNs have a loop in their hidden layer which is connected to the output of the hidden layer of previous data points. Those connections are associated with different weights and biases. In this way, the networks are able to take into account information from previous n -periods of the sequential data.

The RNNs constructed for this thesis use twelve neurons for the input layer. This corresponds to the twelve input variables from section 2.3. The single hidden layer consists of five neurons. The logic behind is mathematically arbitrary. The five neurons correspond to the four categories from section 5 – volatility, liquidity, capital flows and macroeconomics plus one neuron for other possible variables not identified in this research. The output layer consists of only one neuron, which corresponds to the binary variable characterizing the returns. Figure 11 gives an illustrative example of the form of an RNNs. Detailed explanation of the technique can be found in Raschka & Mirjalili (2017).

The models use the following specifications:

- **Hidden layers:** one
- **Sequence length:** two
Explanation: The algorithm incorporates the information of the past two valid data points.
- **Activation function for the hidden layer:** tanh
- **Activation function for output layer:** linear
Remark: The output values from this activation function bigger than 0.5 are then classified as 1. Those smaller than 0.5 are classified as 0.
- **Cost function:** mean squared errors
- **Optimizer:** adaptive moment estimation (adam)
Explanation: The method for optimizing the cost function. Adam is a stochastic optimization technique similar to the stochastic gradient descend (SGD) (Kingma & Ba, 2014).
- **Epochs:** 10
Explanation: An epoch is when the whole training dataset is used by the algorithm once.
- **Batch size:** 32
Explanation: Divisions of the whole dataset within one epoch. This variable defines how much data points are taken into account before updating the weights and biases.

Apart from the boundaries associated with RNNs¹⁰, some of the considerable limitations of the approach of this thesis include the choice of hidden layers as well as neurons. There were no prior tests and comparison of the accuracy which could have been used as an argument for the current specification of the model. Furthermore, no tests were done with different combinations of activation functions for the hidden and output layers. Directly using a sigmoid activation function could prove to be more effective when dealing with binary classification problems. Another possible room for optimization is the optimal number of epochs and batches.

Due to the limited computational power and time resources, such a research remains beyond the scope of this thesis.

6.6. Long Short-Term Memory (LSTM)

The LSTM algorithm is closely related to the RNN. It builds on the insights of the recurrent neural networks by dealing with one of the main problems of the RNNs, the vanishing and exploding gradient issue. By construction, when an RNN model takes into account multiple past data points, the hidden layer of the RNN model is connected to the hidden layer of a neural network from a previous data point. The hidden layer of this previous data point is again connected to the hidden layer of its preceding data point and so on. Those connections are again represented with weights and biases. In the process of backpropagation when there are multiple weights less than 1, the gradient becomes very small. Similarly, the exploding gradient problem arises when the weights are larger than 1 and the gradient is extremely high.

The LSTMs overcomes those issues by distinguishing between long-term data and short-term data. The information about the long-term data are summarized as a single value known as the long-term memory. Likewise, the data for the short-term is given as a value known as short-term memory. Similarly to the RNNs, the hidden layer of the LSTM links to information from past data points. This information is included in the values of the long-term and short-term memories. There are no weights associated with the long-term memory, whereas the algorithm assigns biases and weights to the short-term memory.

¹⁰ Some of the main issues with RNN include the exploding and vanishing gradient problems (Pascanu, Mikolov, & Bengio, 2013).

7. Comparison and Results

The input variables as well as the short-term memory first go into the so called *forget gate*, a sigmoid activation function, which determines how much to keep from the long-term memory. The output of the gate is a value between 0 and 1, which is multiplied with the long-term memory. The algorithm then proceeds with a structure known as *input gate*, which determines what percentage and how much of the short term memory will be remembered as long-term memory. The inputs for this gate are again the input variables and the short-term memory, the values of which are connected to weights and biases. The output of the gate again updates the long-term memory. The final stage of the algorithm uses the information from the updated long-term memory and the short-term memory and generates a prediction. This output also resembles the short-term memory for the next data point.

In other words, the mathematics build on the concept of the tanh and the sigmoid functions, which control how much of the long- and the short-term memory are updated by every new data point (Raschka & Mirjalili, 2017). The algorithm then combines the information of the two “memories” and returns a value.

The model in this thesis uses identical specifications as the RNN. The main difference is that the LSTM takes the past 22 data points. This number is arbitrarily chosen. The intention is to approximately observe the last month of data in order to make a prediction. Further research on the optimal period for the different factor portfolios has not been conducted.

7. Comparison and Results

The results of the models are presented in Appendix 1. The Appendix shows tables with basic statistics, performance ratios and quantiles as well as the predictions accuracy. Graphical representations of the time series of the timed portfolios compared to the factor portfolio are seen in Appendix 2 (Currency Value Factor), Appendix 3 (Currency Carry Factor) and Appendix 4 (Currency Momentum Factor).

7.1. Value

After comparing the Sharpe ratios from the tables in Appendix 1, the best risk-return trade-off of the value factor is achieved with long and short positions and quarterly rebalancing. This confirms the view that the REERs as well as the concept of purchasing power parity (PPP) are

7. Comparison and Results

indeed more meaningful for long run convergence of exchange rates to an equilibrium. The long/short combination of the positions in the factor portfolio also has the biggest monthly return. Interestingly, the short only composition of the factor portfolios yields the highest Sortino ratios. The short only portfolios also possess the least standard deviation. Furthermore, this combination also considerably limits the downside risks of the factor. This suggests that only shorting currencies which are relatively overvalued, delivers better investment performance to only going long currencies, which are undervalued. Thus, the REERs seem to be a better equilibrium concept for overvalued currencies. Additionally, a negative skewness is observed for portfolios with long only positioning, whereas positive skewness is detected in short only portfolios. This difference does not depend on the holding period.

The timed portfolios using logistic regression do not seem to outperform the static factor portfolios. An exception could be found individually in portfolios with only long positions. For such portfolios the logistic regression also manages to improve the negative side of the distribution of the factor returns (see Table A1.L-2 in Appendix 1).

The machine learning models manage to notably enhance the Sharpe ratio of the value factor and provide approximately a monthly return of 0.4 per unit of risk. The models seem to demonstrate an ability to mitigate the downside risk of the factor for every rebalancing period and all long/short combinations. This also can be seen in the graphical depictions of the models in Appendix 2.

The accuracy of the predicted variables for most of the machine learning models lies around 80%. This holds for every factor construction. The accuracy of the timing for both negative and positive return estimates of the machine learning algorithms is similar. For comparison, Tables A1.L-3, A1.LS-3 and A1.S-3 in Appendix 1 also provide the percentage of positive returns in the static factor. This corresponds to the accuracy of a naive model solely predicting only positive returns. The overall accuracy of such a model is approximately 55%, and thus slightly lower than the percentage of accurate predictions achieved by the logistic regression.

The portfolios timed with neural networks seem to outperform the KNN, SVM and RF. To summarize, it can be inferred that using machine learning for timing the value factor enhances the performance of the factor. Moreover, the algorithms also deliver superior performance than a logistic regression in timing the factor.

7.2. Carry

Among the studied risk factors, the currency carry factor generate the highest returns. The factor exhibits the highest Sharpe ratios when constructed with both long and short positions. As the holding period decreases, the Sharpe ratios increase. A larger holding period is associated with an increase in the risk of significant performance declines. This observation supports the peso problem narrative described in section 3.2. In other words, extreme negative returns are more characteristic for longer holding periods. When considering portfolios with short only exposure, the Sortino ratios are considerably higher than the corresponding Sharpe ratios. This indicates that the peso risk associated with the factor may stem only from long positions.

The timing of the factor with logistic regression fails to deliver superior performance in the same way as the value factor. In contrast, the traditional model is not able to predict extreme negative returns. Both, Sharpe ratios as well as Sortino ratios are remarkably worse compared to the static factor statistics (see Tables A1.L-2, A1.LS-2 and A1.S-2). Furthermore, as can be seen in Appendix 3, the logistic regression even shift the distribution of the carry returns slightly to the left in some cases. In terms of categorizing accuracy, the traditional approach provides results not better than the naive strategy of always classifying returns as positive.

The machine learning models also do not prove to be very beneficial in timing the factor. The performance is similar to that of the traditional regression. In this setting, the neural networks-based algorithms did not provide superior results over the other ML techniques. Comparing the Sharpe ratios, the only case in which the machine learning models improve the risk-return trade off of the carry factor is for short only portfolios and quarterly holding period. Nevertheless, the algorithms seem to influence the skewness and kurtosis of the carry distribution. Although the extreme returns are not captured by any model, for longer holding periods and portfolios with short positions, the models do shift the returns distribution to the right. This can be seen in Appendix 3 as well as in Table A1.S-1 in Appendix 1. The analysis points out that the currency carry factor only can be partially timed using such machine learning techniques. The models do improve the strategy's statistical characteristics. This is true for the worst performing factor constructions of the carry factor. Additionally, in most of the settings the machine learning models provide similar results compared to the more traditional approach.

7.3. Momentum

As previously mentioned, the factor portfolios ranked on past 1-month and past 3-month performance have expected monthly returns near zero. Some of the combinations even possess slightly negative statistical means. This comes with a standard deviation similar to the standard deviation of the currency value factor. Portfolios with short positions tend to outperform those with only long positions. This is true particularly for more frequent rebalancing periods. Hence, the short-term trends in depreciating currencies is more robust to exploit in comparison to the short-term trends in appreciating currencies.

The timing of the portfolios using the more traditional approach improve the mean of the factors while at the same time keep the standard deviation unchanged for both, the 1m-momentum and 3m-momentum factor. This results in Sharpe ratios between 0.04 and 0.22, which are better than the Sharpe ratios of the comparable timed value factor. Furthermore, for portfolios build solely on long positions the logistic regression manage to increase the threshold of the 0.1, 0.01 and 0.001 quantiles and thus, reduce the negative side of the factor. The only exception, where the factor timing doesn't prove superior to the static factor, is found for short only portfolios with monthly holding period for the 3m-momentum factor. Overall, the logistic regressions are able to predict approximately 55-65% of the returns.

The timing of the factor with machine learning algorithms also improve the performance of the factors. The statistical mean of the timed factor is positive. The models provide similar risk-return trade-offs as those with the value factor. The Sharpe Ratios range from 0.35 to 0.5 for both 1m-momentum and 3m-momentum. Higher Sortino ratios for timed portfolios with long positions are observed. As Table A1.L-2 in Appendix 1 suggests the machine learning models further increase the quantile values. The RNNs seem to perform better in most of the cases. The worst among the ML models is the KNN.

The results suggest that the factor timing of the 1m-momentum and 3m-momentum factor significantly enhances the static factor performance. The main effect of the timing is on transforming the mean of the factor returns distribution from slightly negative to positive. No considerable difference in the standard deviations is observed. Appendix 4 graphically illustrates that the 1m-momentum and 3m-momentum factors are turned into profitable strategies by both traditional as well as machine learning models. Still, the ML techniques outperform the logistic regression.

7. Comparison and Results

The 12m-momentum factor produces the highest expected monthly returns with similar to the other two momentum factors variations deviation. Similarly, only shorting currencies with the lowest 1-year momentum seems to be the best performing structure of the factor. Additionally, the longer the holding period the higher the monthly returns seem to be. This implies that long-term trends in exchange rate dynamics persist for longer periods. Still for the examined period the factor experiences a slightly negative risk-return trade-offs.

The timing of the factor using traditional statistical models is able to shift the distribution of returns to the right for long only portfolios. However, the regression does not provide better statistics for portfolios where short positions are present. Furthermore, where shorting is involved, the logistic regression hardly manages to improve the tail risks of the factor. In the case of long only combinations, the factor timing using logistic regression yields Sharpe ratios between 0.1 and 0.13 in comparison to the factor Sharpe ratios of around 0 for the static factor approach. The overall accuracy of the logistic regressions is around 60%, compared to 50% positive returns of the factor and an accuracy of around 80% of the machine learning models.

The timing with machine learning algorithms hugely improves the means of the 12m-momentum distribution, especially for long only portfolios. The presence of short positions in a portfolio reduces the timing profitability. This implies that short positions are harder to predict given the twelve input variables. The Sharpe ratios for portfolios with short exposure are less than those of the timed currency value factor but still better than the static 12m-momentum factor. Especially for long only portfolios the models transform the distribution of returns in a profitable way. Although the ML algorithms provide better risk-return characteristics for short only portfolios, they do not predict well extremes in negative returns. Notably, the downside of short only portfolios is much less than the downside of long only portfolios. The neural network models again slightly outperform the other techniques.

In summary, the results for the 12m-momentum factor suggest that the traditional approaches can be partly used to time the factor and reduce its downside risks. This is particularly true for portfolios with long only positions. The machine learning models prove to be superior to the logistic regressions in every setting. However, for portfolios with only short exposure, none of the models manage to reduce the negative impact of extreme events.

8. Limitations

There are certain limitations in this research associated with the data, the factors construction, the specifications of the statistical models as well as the input variables used in forecasting the returns.

8.1. Data

Currencies can be affected by natural events, as well as geopolitical and economic decisions and man made disasters. In this thesis I do not additionally account for pegged currencies, hyperinflation, liquidity issues, trading bans or any kind of natural or man made cataclysms. I solely rely on the assumption that if valid forward market data were provided from Bloomberg, it must have been possible to engage into a forward contract. The thesis solely considers implicit transaction costs. More specifically, the bid-ask spreads are taken into account. However, it does not incorporate explicit costs such as brokerage costs, taxes, exchange fees or others, which have a negative effect on factor returns.

8.2. Factors Construction

For there are many different perceptions on how to calculate value in the currency markets, each methodology, including the REER, has its unique limitations. The most relevant issue in regard to the REER is the fact that the daily time series of the indices are driven by exchange rates and not by daily macroeconomic data. The rebalancing of the weights occurs at a more infrequent interval. Some of the limitations in the construction of the factor are that there are also other models for currency equilibrium, which are not presented and discussed in this thesis. Examples include concepts like PEER, FEER etc. Nevertheless, the main ideas behind these models are very much similar to those presented here.

Baku et al. (2020) construct the value factor as a weighted average of multiple portfolios and build on different equilibrium approaches. This would have been an alternative approach, which may capture both, short-term as well as long-term dynamics. It also opens the door for further investigating various rebalancing periods.

Forming the carry factor returns entails a frequent short exposure to currencies such as the Botswana Pule and the Uganda Schilling. This may be due to market limitations, such as liquidity, the implementation of capital controls or other measures resulting from social,

economic or political events that influence the obtained forward and spot rates. Additionally, the factor incorporates several currencies, which have been pegged to other currencies throughout the period of analysis. Examples include the Jordanian Dinar (JOD), the Croatian Kuna (HRK) and the Bulgarian Lev (BGN).

8.3. Variables used for forecasting factor returns

Although the literature identifies some main drivers of the factor performance, it is quite hard to implement them in a day-to-day model, which guides investment decisions. There may be other time series explaining better than the factors. However, the primary goal of this thesis is not to identify such variables but to analyze the relative performance of machine learning models within the framework of factor timing.

One of the main issues is the NFCI Index, which is calculated as an average of other indices. One of those other indices is another input variable, the VIX. Although the weight of the VIX is less than 4% in the NFCI Index, the data analysis shows a strong correlation between the NFCI and the VIX. Furthermore, the index is published on Wednesdays and reflects the data of the preceding week. In other words, this variable includes a reporting lag. In this thesis, the weekly time series are converted to daily series by utilizing the value published on a Wednesday as representation for the period spanning from the last Friday prior to the publication until the first Thursday following the publication. It is important to note that these time series impose limitations on the practical implementation of the approach on the financial markets because the latest data is not always present when taking the investment decision.

8.4. Models

Most of the parameters, defining the statistical models, are standard. Some basic pre-tests for choosing optimal parameters were conducted. Nevertheless, this thesis doesn't go one level further by conducting an in-depth technical analysis to identify the best parameters.

9. Conclusion

I investigate the benefits of factor timing using machine learning in currency factor strategies. Three risk factors on the FX markets are identified, value, carry and momentum. Each of the factors is captured with different portfolio constructions (long only, long/short and short only positions) and different holding periods. Furthermore, three different variations of the

9. Conclusion

momentum factor are analyzed, momentum built on past month performance, 3m-momentum build on three months past performance and 12m-momentum based on past 1-year performance. After identifying possible drivers of factor returns, traditional as well as machine learning models are implemented. Timed factor portfolios are then constructed based on the models' forecasts.

The results suggest that factor timing with both traditional as well as machine learning models improves the performance of the currency value and momentum factors. The machine learning techniques significantly outperform the logistic regression. The timing of the carry factor using logistic regression does not enhance the performance of the factor. Similarly, the machine learning models prove beneficial only for some of the variants of the carry factor portfolios. Those variants are the worst performing among the analyzed constructions of the carry factor.

Due to the limited scope of the thesis, further study opportunities exist, which can use the current findings as a research basis. Superior results in timing the factors may emerge with the use of other, more advanced statistical models or different model specifications. Also, the general approach of using the algorithms for classification of returns can be challenged with a regression approach. The use of different input variables may also be of interest for research. A study focused on a more praxis relevant approach by incorporating explicit transaction costs and considering further trade restrictions could also broaden the insights of this thesis. Despite its limitations, the thesis remains a valuable contribution to the existing literature on currency risk factors.

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Appendix 1: Results

Description: This appendix presents tables of different performance statistics with regard to the timed factor time-series and the static factors time-series.

Table A1.L-1: *Summary statistics of timed factors for portfolios with only long positions (monthly)*

Table A1.L-2: *Risk measures of timed factors for portfolios with only long positions (monthly)*

Table A1.L-3: *Accuracy of prediction for portfolios with only long positions*

Table A1.LS-1: *Summary statistics of timed factors for portfolios with long and short positions (monthly)*

Table A1.LS-2: *Risk measures of timed factors for portfolios with long and short positions (monthly)*

Table A1.LS-3: *Accuracy of prediction for portfolios with long and short positions*

Table A1.S-1: *Summary statistics of timed factors for portfolios with only short positions (monthly)*

Table A1.S-2: *Risk measures of timed factors for portfolios with only short positions (monthly)*

Table A1.S-3: *Accuracy of prediction for portfolios with only short positions*

Appendix 1.L.

Portfolios with only long positions

Panel A: Value															
	monthly				bimonthly				quarterly						
	Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF			
Mean	0.2%	0.3%	0.9%	1.1%	1.0%	1.2%	1.1%	0.2%	0.2%	0.8%	0.8%	0.9%	0.2%	0.2%	0.7%
Std	2.9%	2.9%	2.8%	2.7%	2.8%	2.7%	2.7%	2.1%	2.1%	2.0%	2.0%	2.0%	1.7%	1.7%	1.6%
Min	-23.4%	-14.7%	-14.7%	-14.7%	-14.7%	-14.7%	-14.7%	-12.9%	-7.5%	-9.6%	-7.0%	-7.0%	-8.5%	-6.7%	-6.7%
Skew	-1.0	0.8	0.9	1.1	1.0	1.1	1.0	-0.8	0.5	0.9	0.9	1.0	-0.6	0.1	0.6
Kurtosis	7.7	7.3	8.0	8.3	8.2	8.7	8.6	4.5	3.9	4.1	4.1	4.1	3.4	3.0	3.3
Panel B: Carry															
	monthly				bimonthly				quarterly						
	Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF			
Mean	2.1%	1.4%	1.5%	1.5%	1.5%	1.5%	1.5%	1.8%	1.1%	1.3%	1.3%	1.3%	0.5%	0.2%	0.7%
Std	3.4%	3.8%	3.7%	3.7%	3.7%	3.7%	3.7%	6.4%	6.6%	6.5%	6.5%	6.5%	2.6%	2.6%	2.5%
Min	-27.1%	-27.1%	-27.1%	-27.1%	-24.2%	-27.1%	-27.1%	-29.4%	-29.4%	-29.4%	-29.4%	-29.4%	-80.3%	-80.3%	-80.3%
Skew	-1.4	-0.5	-0.1	0.0	0.1	-0.4	-0.4	-30.4	-27.9	-28.4	-28.4	-28.4	-8.0	-6.6	-7.1
Kurtosis	7.9	3.6	3.2	3.1	2.9	3.6	3.7	1275.8	1140.0	1170.6	1170.9	1168.5	224.3	208.7	242.7
Panel C: 1m-Mom															
	monthly				bimonthly				quarterly						
	Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF			
Mean	-0.2%	0.5%	1.1%	1.3%	1.2%	1.3%	1.3%	-0.1%	0.4%	0.8%	1.0%	0.9%	0.0%	0.5%	0.8%
Std	3.5%	3.5%	3.4%	3.3%	3.4%	3.3%	3.3%	2.7%	2.7%	2.6%	2.5%	2.5%	2.2%	2.2%	2.1%
Min	-21.7%	-16.2%	-17.8%	-15.3%	-17.8%	-17.8%	-15.3%	-15.7%	-11.7%	-11.1%	-10.0%	-11.1%	-15.1%	-9.2%	-9.2%
Skew	-1.0	0.6	0.8	0.7	0.7	0.5	0.8	-1.3	0.7	0.9	1.0	1.0	-1.6	1.1	1.4
Kurtosis	4.4	4.5	4.7	5.0	4.9	5.5	5.0	4.3	4.3	4.3	4.4	4.4	6.0	5.8	5.9
Panel D: 3m-Mom															
	monthly				bimonthly				quarterly						
	Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF			
Mean	-0.2%	0.5%	1.2%	1.4%	1.3%	1.5%	1.5%	-0.1%	0.3%	1.0%	1.1%	1.1%	0.0%	0.3%	0.9%
Std	3.8%	3.8%	3.6%	3.5%	3.6%	3.5%	3.5%	2.9%	2.9%	2.8%	2.7%	2.7%	2.3%	2.3%	2.1%
Min	-37.4%	-37.4%	-19.6%	-21.1%	-13.8%	-13.8%	-13.8%	-19.7%	-19.7%	-10.8%	-16.8%	-9.4%	-15.1%	-15.1%	-9.4%
Skew	-1.6	0.4	1.5	1.5	1.6	1.7	1.7	-1.4	0.1	1.1	1.0	1.1	-1.4	-0.3	1.1
Kurtosis	9.1	9.6	9.7	10.4	9.8	10.5	10.4	4.9	5.1	4.9	5.2	5.0	5.0	5.3	5.1
Panel E: 12m-Mom															
	monthly				bimonthly				quarterly						
	Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF			
Mean	-0.2%	0.5%	1.2%	1.5%	1.4%	1.5%	1.5%	0.1%	0.4%	0.9%	0.9%	1.0%	0.1%	0.4%	0.9%
Std	3.9%	3.9%	3.7%	3.7%	3.7%	3.6%	3.6%	2.9%	2.9%	2.7%	2.7%	2.7%	2.7%	2.7%	2.6%
Min	-34.1%	-15.3%	-15.3%	-14.5%	-14.5%	-14.5%	-14.5%	-20.9%	-14.2%	-9.8%	-18.3%	-14.2%	-80.0%	-80.0%	-80.0%
Skew	-1.3	1.3	1.3	1.4	1.4	1.4	1.4	-1.3	1.1	1.2	1.0	1.1	-7.1	-5.3	-6.7
Kurtosis	7.9	7.7	8.3	8.7	8.5	8.8	8.8	5.0	4.5	4.6	4.7	4.8	179.1	187.2	232.3

Table A1.L-1: Summary statistics of timed factors for portfolios with only long positions (monthly).

Panel A: Value																					
monthly											bimonthly					quarterly					
Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF	RNN	LSTM	
Sharpe	0.06	0.10	0.33	0.39	0.37	0.44	0.41	0.11	0.10	0.40	0.42	0.46	0.49	0.49	0.14	0.12	0.40	0.39	0.44	0.47	0.45
Sortino	0.06	0.14	0.47	0.56	0.52	0.61	0.57	0.12	0.15	0.65	0.67	0.80	0.83	0.85	0.16	0.17	0.58	0.56	0.66	0.72	0.69
q(0.001)	-19.7%	-11.5%	-11.4%	-11.1%	-11.4%	-11.4%	-11.4%	-11.0%	-7.2%	-6.7%	-6.7%	-6.6%	-6.6%	-6.6%	-7.6%	-6.1%	-6.0%	-6.1%	-6.0%	-6.0%	-6.0%
q(0.01)	-10.0%	-7.8%	-7.4%	-6.7%	-7.1%	-6.6%	-6.9%	-7.0%	-5.6%	-4.4%	-4.5%	-4.0%	-3.8%	-3.8%	-5.4%	-4.9%	-3.9%	-3.9%	-3.6%	-3.1%	-3.1%
q(0.1)	-2.5%	-2.4%	-1.1%	-0.9%	-1.0%	-0.7%	-0.8%	-1.9%	-2.0%	-0.7%	-0.7%	-0.6%	-0.5%	-0.5%	-1.5%	-1.5%	-0.6%	-0.6%	-0.5%	-0.5%	-0.5%
Panel B: Carry																					
monthly											bimonthly					quarterly					
Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF	RNN	LSTM	
Sharpe	0.61	0.37	0.41	0.40	0.39	0.40	0.28	0.16	0.20	0.20	0.19	0.19	0.20	0.20	0.18	0.07	0.24	0.24	0.27	0.27	0.27
Sortino	0.61	0.56	0.70	0.71	0.61	0.65	0.14	0.12	0.13	0.13	0.13	0.13	0.14	0.16	0.08	0.25	0.25	0.28	0.28	0.29	
q(0.001)	-22.5%	-22.5%	-20.3%	-17.5%	-13.9%	-20.7%	-22.5%	-16.1%	-16.1%	-15.1%	-15.7%	-13.0%	-16.1%	-14.2%	-9.9%	-9.6%	-9.2%	-9.4%	-9.1%	-9.6%	-9.1%
q(0.01)	-8.4%	-7.1%	-6.2%	-6.2%	-6.1%	-6.6%	-6.1%	-8.0%	-6.8%	-5.9%	-5.8%	-5.9%	-5.9%	-5.5%	-8.0%	-5.8%	-4.2%	-4.2%	-3.8%	-3.9%	-3.9%
q(0.1)	-1.4%	-3.1%	-3.0%	-3.0%	-3.0%	-3.0%	-3.0%	-1.2%	-2.8%	-2.5%	-2.6%	-2.6%	-2.6%	-2.6%	-2.3%	-2.4%	-2.1%	-2.1%	-2.0%	-2.0%	-2.0%
Panel C: 1m-Mom																					
monthly											bimonthly					quarterly					
Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF	RNN	LSTM	
Sharpe	-0.06	0.15	0.31	0.39	0.34	0.41	0.39	-0.04	0.13	0.32	0.38	0.36	0.40	0.40	-0.01	0.22	0.35	0.40	0.38	0.42	0.37
Sortino	-0.07	0.24	0.52	0.61	0.55	0.59	0.63	-0.04	0.22	0.57	0.70	0.66	0.75	0.75	-0.02	0.39	0.64	0.73	0.70	0.79	0.74
q(0.001)	-18.4%	-14.4%	-13.5%	-13.5%	-14.1%	-14.9%	-13.5%	-14.1%	-9.9%	-8.7%	-8.1%	-8.7%	-8.1%	-8.3%	-11.8%	-7.6%	-6.5%	-6.5%	-6.5%	-6.4%	-6.4%
q(0.01)	-12.7%	-8.4%	-7.2%	-6.9%	-7.0%	-7.3%	-6.9%	-9.9%	-6.9%	-5.2%	-4.7%	-4.8%	-4.4%	-4.4%	-8.7%	-4.7%	-3.9%	-3.6%	-3.7%	-3.5%	-3.5%
q(0.1)	-3.8%	-3.1%	-2.4%	-2.1%	-2.3%	-1.9%	-2.1%	-3.0%	-2.4%	-1.9%	-1.7%	-1.7%	-1.7%	-1.6%	-2.2%	-1.7%	-1.4%	-1.3%	-1.3%	-1.2%	-1.4%
Panel D: 3m-Mom																					
monthly											bimonthly					quarterly					
Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF	RNN	LSTM	
Sharpe	-0.06	0.13	0.34	0.40	0.36	0.44	0.42	-0.02	0.09	0.36	0.41	0.39	0.44	0.43	0.01	0.13	0.37	0.41	0.40	0.46	0.44
Sortino	-0.07	0.19	0.62	0.69	0.67	0.82	0.77	-0.02	0.12	0.66	0.72	0.72	0.85	0.79	0.01	0.18	0.65	0.71	0.72	0.84	0.82
q(0.001)	-24.3%	-20.5%	-12.7%	-11.9%	-11.8%	-11.8%	-11.8%	-16.6%	-14.4%	-8.3%	-8.3%	-8.3%	-7.8%	-8.1%	-12.4%	-12.2%	-7.3%	-7.1%	-7.0%	-6.2%	-6.2%
q(0.01)	-13.2%	-8.9%	-6.6%	-6.5%	-6.6%	-6.2%	-6.4%	-10.5%	-7.7%	-5.2%	-4.9%	-5.1%	-4.7%	-4.9%	-7.9%	-6.6%	-4.6%	-4.5%	-4.5%	-4.0%	-3.9%
q(0.1)	-4.1%	-3.3%	-2.2%	-2.0%	-2.2%	-1.7%	-1.8%	-3.2%	-2.9%	-1.8%	-1.7%	-1.7%	-1.6%	-1.7%	-2.6%	-1.9%	-1.2%	-1.2%	-1.2%	-1.1%	-1.2%
Panel E: 12m-Mom																					
monthly											bimonthly					quarterly					
Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF	RNN	LSTM	
Sharpe	-0.04	0.12	0.33	0.40	0.37	0.41	0.41	0.02	0.13	0.34	0.33	0.39	0.40	0.41	0.03	0.13	0.30	0.30	0.35	0.37	0.36
Sortino	-0.04	0.20	0.55	0.67	0.64	0.68	0.68	0.02	0.23	0.67	0.61	0.74	0.78	0.80	0.03	0.17	0.33	0.32	0.36	0.37	0.36
q(0.001)	-23.9%	-13.3%	-13.3%	-13.2%	-13.2%	-13.2%	-13.2%	-14.3%	-7.9%	-7.9%	-7.9%	-8.4%	-7.9%	-7.9%	-12.6%	-8.1%	-8.7%	-8.7%	-8.1%	-8.1%	-8.1%
q(0.01)	-13.2%	-9.1%	-8.0%	-7.1%	-7.2%	-7.1%	-7.1%	-11.1%	-6.0%	-5.0%	-5.2%	-4.9%	-4.9%	-4.9%	-10.6%	-4.7%	-4.3%	-4.3%	-4.1%	-4.0%	-4.3%
q(0.1)	-3.9%	-3.5%	-2.4%	-1.9%	-2.1%	-1.9%	-1.9%	-3.0%	-2.6%	-1.8%	-1.9%	-1.7%	-1.6%	-1.6%	-2.5%	-2.1%	-1.5%	-1.6%	-1.4%	-1.3%	-1.3%

Table A1.L-2: Risk measures of timed factors for portfolios with only long positions (monthly).

Panel A: Value													
	monthly				bimonthly				quarterly				
	Dummy	Log	KNN	SVM	RF	RNN	LSTM	Dummy	Log	KNN	SVM	RF	LSTM
overall Accuracy	52%	58%	78%	82%	80%	86%	85%	56%	59%	82%	84%	85%	87%
True Positives	52%	58%	77%	84%	81%	87%	84%	56%	61%	84%	82%	86%	88%
True Negatives	0%	59%	78%	81%	79%	86%	85%	0%	54%	80%	86%	84%	86%
Panel B: Carry													
	monthly				bimonthly				quarterly				
	Dummy	Log	KNN	SVM	RF	RNN	LSTM	Dummy	Log	KNN	SVM	RF	LSTM
overall Accuracy	84%	82%	83%	83%	84%	84%	83%	81%	80%	85%	85%	85%	84%
True Positives	84%	84%	87%	87%	88%	87%	87%	81%	84%	88%	88%	87%	89%
True Negatives	0%	34%	49%	47%	51%	53%	48%	0%	43%	63%	64%	62%	59%
Panel C: 1m-Mom													
	monthly				bimonthly				quarterly				
	Dummy	Log	KNN	SVM	RF	RNN	LSTM	Dummy	Log	KNN	SVM	RF	LSTM
overall Accuracy	49%	60%	72%	78%	74%	80%	78%	48%	63%	77%	82%	79%	83%
True Positives	49%	60%	71%	77%	73%	80%	77%	48%	62%	76%	81%	78%	79%
True Negatives	0%	61%	73%	79%	75%	81%	79%	0%	63%	78%	84%	81%	84%
Panel D: 3m-Mom													
	monthly				bimonthly				quarterly				
	Dummy	Log	KNN	SVM	RF	RNN	LSTM	Dummy	Log	KNN	SVM	RF	LSTM
overall Accuracy	49%	61%	73%	80%	76%	83%	82%	54%	62%	78%	83%	80%	85%
True Positives	49%	60%	72%	79%	74%	81%	80%	54%	63%	78%	84%	81%	84%
True Negatives	0%	63%	75%	80%	77%	84%	83%	0%	60%	77%	83%	80%	86%
Panel E: 12m-Mom													
	monthly				bimonthly				quarterly				
	Dummy	Log	KNN	SVM	RF	RNN	LSTM	Dummy	Log	KNN	SVM	RF	LSTM
overall Accuracy	48%	59%	74%	80%	77%	82%	82%	51%	62%	78%	78%	81%	84%
True Positives	48%	64%	73%	79%	77%	80%	82%	51%	65%	78%	76%	81%	85%
True Negatives	0%	58%	75%	81%	78%	85%	81%	0%	60%	78%	82%	81%	83%

Table A1.L-3: Accuracy of prediction for portfolios with only long positions.

Appendix 1.LS. Portfolios with long and short positions

Panel A: Value																
monthly							bimonthly							quarterly		
Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	LSTM
Mean	0.6%	0.1%	1.1%	1.1%	1.2%	1.1%	0.6%	0.2%	0.8%	0.8%	0.9%	1.0%	1.0%	0.6%	0.3%	0.8%
Std	3.2%	3.3%	3.1%	3.1%	3.0%	3.1%	2.3%	2.4%	2.2%	2.2%	2.2%	2.2%	2.2%	1.9%	2.0%	1.9%
Min	-22.9%	-19.4%	-19.4%	-19.4%	-19.4%	-19.4%	-11.9%	-12.9%	-12.9%	-12.9%	-12.9%	-12.9%	-12.9%	-8.3%	-9.2%	-9.2%
Skew	-0.5	0.1	0.6	0.5	0.6	0.4	0.1	-0.4	-0.1	-0.3	0.0	0.0	-0.1	0.3	-0.5	-0.4
Kurtosis	6.4	5.5	6.0	6.3	6.1	6.4	3.7	3.4	4.5	4.8	4.6	5.0	5.0	2.0	2.4	3.3
Panel B: Carry																
monthly							bimonthly							quarterly		
Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	LSTM
Mean	3.2%	1.5%	1.6%	1.6%	1.5%	1.5%	2.5%	1.1%	1.3%	1.2%	1.3%	1.2%	1.2%	1.0%	-0.1%	0.5%
Std	4.0%	4.9%	4.9%	4.9%	4.9%	4.9%	6.6%	7.0%	7.0%	7.0%	7.0%	7.0%	7.0%	2.7%	2.8%	2.8%
Min	-24.1%	-46.0%	-24.1%	-24.1%	-46.0%	-39.2%	-296.0%	-296.0%	-296.0%	-296.0%	-296.0%	-296.0%	-296.0%	-80.0%	-80.0%	-80.0%
Skew	0.4	-0.3	0.1	0.2	0.1	-0.3	-28.2	-23.4	-23.9	-23.7	-23.8	-23.7	-23.6	-6.4	-5.4	-5.5
Kurtosis	9.3	4.9	4.5	4.4	4.5	4.7	1158.2	905.2	926.8	920.4	922.7	918.8	915.8	198.2	144.2	159.2
Panel C: 1m-Mom																
monthly							bimonthly							quarterly		
Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	LSTM
Mean	0.0%	0.4%	0.9%	1.1%	1.3%	1.2%	0.0%	0.2%	0.6%	0.7%	0.7%	0.8%	0.7%	0.0%	0.2%	0.7%
Std	3.6%	3.6%	3.5%	3.4%	3.4%	3.4%	2.6%	2.6%	2.5%	2.5%	2.5%	2.5%	2.5%	2.1%	2.0%	2.0%
Min	-20.5%	-21.5%	-21.5%	-21.5%	-21.5%	-21.5%	-16.1%	-11.2%	-11.2%	-11.2%	-11.2%	-11.2%	-11.2%	-13.7%	-9.6%	-9.6%
Skew	-0.4	0.4	0.3	0.3	0.3	0.3	-0.6	0.5	0.5	0.5	0.5	0.5	0.6	-1.0	0.8	0.8
Kurtosis	3.3	3.3	3.5	3.7	3.5	3.7	3.4	3.3	3.3	3.5	3.4	3.6	3.4	5.7	5.5	6.0
Panel D: 3m-Mom																
monthly							bimonthly							quarterly		
Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	LSTM
Mean	0.0%	0.5%	1.1%	1.2%	1.5%	1.3%	0.0%	0.3%	0.9%	1.0%	0.9%	1.0%	1.1%	0.0%	0.2%	0.9%
Std	4.0%	4.0%	3.8%	3.8%	3.7%	3.8%	2.9%	2.9%	2.8%	2.7%	2.8%	2.7%	2.7%	2.2%	2.2%	2.0%
Min	-35.3%	-21.9%	-31.8%	-31.8%	-31.8%	-31.8%	-19.3%	-10.0%	-10.3%	-10.0%	-10.3%	-10.0%	-17.6%	-15.5%	-13.2%	-11.5%
Skew	-1.1	0.7	0.9	0.7	0.9	0.8	-1.0	0.7	0.7	0.7	0.7	0.8	0.6	-0.9	-0.4	0.5
Kurtosis	6.6	6.4	6.7	7.3	7.4	7.3	4.1	3.9	4.1	4.3	4.2	4.2	4.6	4.7	4.9	5.6
Panel E: 12m-Mom																
monthly							bimonthly							quarterly		
Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	LSTM
Mean	0.2%	0.2%	1.0%	1.2%	1.4%	1.2%	0.3%	0.1%	0.7%	0.7%	0.8%	0.9%	0.8%	0.3%	0.3%	0.7%
Std	4.0%	4.0%	3.8%	3.8%	3.7%	3.8%	2.7%	2.7%	2.6%	2.6%	2.6%	2.6%	2.6%	2.6%	2.6%	2.5%
Min	-33.5%	-23.6%	-23.6%	-23.6%	-23.6%	-23.6%	-18.2%	-11.1%	-9.8%	-18.2%	-9.9%	-9.4%	-12.4%	-80.7%	-9.7%	-80.7%
Skew	-0.8	0.5	0.7	0.7	0.7	0.6	-0.3	0.4	0.5	0.3	0.5	0.5	0.4	-8.8	8.5	-9.1
Kurtosis	6.4	6.2	6.4	6.8	6.7	6.8	3.4	3.2	3.2	3.4	3.3	3.3	3.4	267.1	256.3	308.6

Table A1.LS-1: Summary statistics of timed factors for portfolios with long and short positions (monthly).

Panel A: Value																					
monthly											bimonthly					quarterly					
Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF	RNN	LSTM	
Sharpe	0.20	0.04	0.32	0.35	0.34	0.41	0.35	0.28	0.08	0.37	0.38	0.41	0.45	0.45	0.33	0.17	0.37	0.39	0.42	0.44	0.41
Sortino	0.25	0.06	0.47	0.48	0.50	0.57	0.47	0.41	0.10	0.47	0.45	0.53	0.55	0.55	0.56	0.22	0.44	0.46	0.50	0.51	0.49
q(0.001)	-18.8%	-16.1%	-14.3%	-14.3%	-14.3%	-15.9%	-10.5%	-10.5%	-10.7%	-10.7%	-11.3%	-10.7%	-10.7%	-10.7%	-7.2%	-8.2%	-8.2%	-8.2%	-8.2%	-8.2%	-8.2%
q(0.01)	-10.5%	-9.3%	-7.7%	-7.7%	-7.5%	-7.7%	-5.9%	-5.9%	-7.1%	-6.1%	-6.2%	-6.0%	-5.9%	-5.9%	-4.7%	-6.1%	-5.4%	-5.4%	-5.4%	-5.4%	-5.4%
q(0.1)	-2.1%	-3.2%	-1.8%	-1.7%	-1.7%	-1.4%	-1.7%	-1.5%	-2.5%	-1.2%	-1.1%	-1.1%	-0.9%	-0.9%	-1.1%	-1.7%	-1.1%	-1.0%	-0.9%	-0.8%	-1.0%
Panel B: Carry																					
monthly											bimonthly					quarterly					
Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF	RNN	LSTM	
Sharpe	0.79	0.31	0.32	0.32	0.30	0.30	0.38	0.15	0.19	0.18	0.18	0.17	0.17	0.38	-0.04	0.18	0.19	0.20	0.21	0.19	
Sortino	1.04	0.45	0.51	0.52	0.50	0.46	0.19	0.12	0.14	0.13	0.13	0.13	0.13	0.36	-0.05	0.19	0.22	0.23	0.23	0.21	
q(0.001)	-18.5%	-22.1%	-21.6%	-20.7%	-22.1%	-22.1%	-13.9%	-14.5%	-15.4%	-15.4%	-16.2%	-15.4%	-15.5%	-8.4%	-11.5%	-11.6%	-9.4%	-10.9%	-10.6%	-11.6%	
q(0.01)	-7.8%	-12.4%	-12.0%	-11.9%	-11.9%	-12.3%	-6.3%	-9.5%	-9.0%	-8.8%	-9.0%	-9.0%	-9.0%	-6.1%	-6.8%	-5.8%	-5.0%	-5.1%	-5.2%	-5.2%	
q(0.1)	-1.1%	-4.3%	-4.2%	-4.2%	-4.3%	-4.2%	-0.9%	-3.7%	-3.5%	-3.6%	-3.6%	-3.6%	-3.6%	-1.7%	-3.2%	-2.6%	-2.5%	-2.5%	-2.5%	-2.6%	
Panel C: 1m-Mom																					
monthly											bimonthly					quarterly					
Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF	RNN	LSTM	
Sharpe	0.00	0.11	0.25	0.32	0.28	0.37	0.34	-0.02	0.09	0.22	0.29	0.26	0.32	0.30	-0.01	0.10	0.25	0.33	0.30	0.35	0.31
Sortino	0.00	0.18	0.38	0.49	0.44	0.55	0.51	-0.02	0.14	0.36	0.47	0.43	0.50	0.51	-0.01	0.17	0.41	0.52	0.49	0.57	0.49
q(0.001)	-17.8%	-14.1%	-14.1%	-12.4%	-13.2%	-13.2%	-12.6%	-13.5%	-9.8%	-9.8%	-9.8%	-9.8%	-9.8%	-9.8%	-11.9%	-8.1%	-8.1%	-8.1%	-8.1%	-7.5%	-8.1%
q(0.01)	-11.4%	-8.9%	-8.5%	-8.4%	-8.5%	-8.3%	-8.3%	-7.8%	-6.4%	-5.7%	-5.6%	-5.7%	-5.7%	-5.3%	-6.8%	-4.9%	-4.5%	-4.4%	-4.3%	-4.3%	-4.4%
q(0.1)	-3.9%	-3.6%	-3.0%	-2.6%	-2.8%	-2.3%	-2.6%	-2.9%	-2.6%	-2.2%	-1.9%	-2.0%	-1.8%	-1.9%	-2.0%	-1.9%	-1.6%	-1.3%	-1.4%	-1.3%	-1.4%
Panel D: 3m-Mom																					
monthly											bimonthly					quarterly					
Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF	RNN	LSTM	
Sharpe	0.00	0.14	0.29	0.35	0.32	0.39	0.35	0.00	0.12	0.32	0.38	0.34	0.38	0.39	0.02	0.09	0.36	0.41	0.39	0.44	0.42
Sortino	0.01	0.22	0.49	0.56	0.53	0.66	0.57	0.01	0.20	0.53	0.61	0.57	0.64	0.62	0.02	0.11	0.54	0.60	0.61	0.69	0.61
q(0.001)	-22.1%	-16.7%	-11.8%	-14.1%	-13.0%	-11.7%	-12.7%	-16.1%	-9.3%	-9.2%	-8.5%	-9.2%	-8.2%	-10.0%	-12.4%	-11.7%	-8.1%	-7.8%	-7.2%	-6.9%	-8.1%
q(0.01)	-12.8%	-9.8%	-7.5%	-7.5%	-7.5%	-7.0%	-7.5%	-10.0%	-7.0%	-6.0%	-5.9%	-5.9%	-5.6%	-5.8%	-7.5%	-6.4%	-4.9%	-4.9%	-4.8%	-4.7%	-4.9%
q(0.1)	-4.0%	-3.5%	-2.9%	-2.5%	-2.7%	-2.3%	-2.5%	-3.1%	-2.9%	-2.1%	-1.9%	-2.0%	-1.9%	-1.8%	-2.2%	-2.2%	-1.5%	-1.3%	-1.4%	-1.2%	-1.3%
Panel E: 12m-Mom																					
monthly											bimonthly					quarterly					
Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF	RNN	LSTM	
Sharpe	0.04	0.04	0.27	0.34	0.31	0.37	0.32	0.11	0.02	0.26	0.28	0.30	0.34	0.31	0.13	0.10	0.25	0.24	0.27	0.32	0.29
Sortino	0.06	0.06	0.40	0.50	0.47	0.52	0.47	0.15	0.03	0.42	0.43	0.49	0.55	0.48	0.12	0.19	0.24	0.23	0.26	0.58	0.27
q(0.001)	-22.8%	-15.4%	-14.3%	-13.7%	-14.3%	-13.7%	-14.3%	-13.1%	-9.3%	-8.8%	-9.3%	-8.9%	-8.2%	-9.5%	-12.4%	-7.8%	-8.8%	-8.8%	-7.9%	-7.8%	-7.9%
q(0.01)	-11.6%	-10.7%	-9.3%	-9.1%	-9.1%	-9.2%	-9.3%	-7.6%	-7.2%	-6.1%	-6.1%	-6.1%	-5.9%	-6.1%	-5.7%	-5.4%	-5.4%	-5.1%	-5.1%	-4.7%	-4.9%
q(0.1)	-3.8%	-4.1%	-3.1%	-2.7%	-2.8%	-2.5%	-2.8%	-2.6%	-3.1%	-2.2%	-2.2%	-2.1%	-2.0%	-2.0%	-2.1%	-2.2%	-1.7%	-1.8%	-1.6%	-1.6%	-1.6%

Table A1.LS-2: Risk measures of timed factors for portfolios with long and short positions (monthly).

Panel A: Value													
	monthly				bimonthly				quarterly				
	Dummy	Log	KNN	SVM	RF	RNN	LSTM	Dummy	Log	KNN	SVM	RF	LSTM
overall Accuracy	61%	57%	76%	79%	79%	85%	81%	64%	60%	81%	84%	84%	87%
True Positives	61%	64%	79%	80%	82%	86%	84%	64%	67%	83%	84%	86%	89%
True Negatives	0%	45%	71%	77%	73%	82%	77%	0%	44%	76%	83%	79%	83%
Panel B: Carry													
	monthly				bimonthly				quarterly				
	Dummy	Log	KNN	SVM	RF	RNN	LSTM	Dummy	Log	KNN	SVM	RF	LSTM
overall Accuracy	85%	85%	85%	85%	85%	85%	84%	82%	82%	86%	84%	85%	82%
True Positives	85%	86%	88%	88%	89%	88%	88%	82%	85%	89%	88%	89%	85%
True Negatives	0%	42%	51%	49%	50%	51%	45%	0%	46%	65%	58%	61%	75%
Panel C: 1m-Mom													
	monthly				bimonthly				quarterly				
	Dummy	Log	KNN	SVM	RF	RNN	LSTM	Dummy	Log	KNN	SVM	RF	LSTM
overall Accuracy	51%	56%	66%	72%	68%	75%	73%	50%	57%	67%	73%	70%	74%
True Positives	51%	58%	67%	72%	69%	76%	74%	50%	57%	66%	72%	69%	73%
True Negatives	0%	55%	66%	72%	68%	74%	72%	0%	56%	68%	73%	70%	74%
Panel D: 3m-Mom													
	monthly				bimonthly				quarterly				
	Dummy	Log	KNN	SVM	RF	RNN	LSTM	Dummy	Log	KNN	SVM	RF	LSTM
overall Accuracy	52%	58%	69%	75%	71%	77%	74%	55%	57%	74%	79%	76%	81%
True Positives	52%	59%	70%	76%	71%	77%	76%	55%	61%	75%	81%	76%	80%
True Negatives	0%	56%	67%	74%	71%	77%	73%	0%	53%	72%	78%	75%	82%
Panel E: 12m-Mom													
	monthly				bimonthly				quarterly				
	Dummy	Log	KNN	SVM	RF	RNN	LSTM	Dummy	Log	KNN	SVM	RF	LSTM
overall Accuracy	51%	55%	72%	79%	76%	82%	77%	54%	57%	74%	77%	79%	84%
True Positives	51%	57%	73%	79%	76%	81%	82%	54%	61%	75%	75%	80%	83%
True Negatives	0%	53%	71%	78%	75%	83%	73%	0%	53%	72%	79%	77%	86%

Table A1.LS-3: Accuracy of prediction for portfolios with long and short positions.

Panel A: Value															
monthly				bimonthly				quarterly							
Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log
Mean	0.5%	0.3%	0.7%	0.8%	0.8%	0.9%	0.4%	0.3%	0.6%	0.6%	0.6%	0.7%	0.7%	0.4%	0.3%
Std	2.3%	2.3%	2.3%	2.2%	2.2%	2.2%	1.7%	1.8%	1.7%	1.7%	1.7%	1.6%	1.6%	1.5%	1.5%
Min	-11.6%	-22.5%	-22.5%	-22.5%	-22.5%	-22.5%	-5.9%	-14.0%	-14.0%	-14.0%	-14.0%	-14.0%	-14.0%	-4.3%	-9.4%
Skew	2.0	-0.8	-1.1	-1.2	-1.2	-1.3	1.9	-1.3	-1.8	-1.6	-1.7	-1.8	-1.7	1.7	-1.5
Kurtosis	12.0	13.4	16.3	18.2	17.4	19.9	8.0	10.2	13.5	13.9	14.1	15.6	15.3	4.9	7.4
Panel B: Carry															
monthly				bimonthly				quarterly							
Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log
Mean	1.1%	0.3%	0.5%	0.6%	0.6%	0.5%	0.7%	0.3%	0.5%	0.4%	0.5%	0.5%	0.4%	0.5%	0.5%
Std	2.7%	2.9%	2.9%	2.9%	2.9%	2.9%	1.8%	2.0%	1.9%	1.9%	1.9%	1.9%	1.9%	1.6%	1.6%
Min	-12.7%	-30.2%	-30.2%	-30.2%	-44.9%	-44.9%	-5.1%	-15.9%	-16.4%	-16.1%	-16.4%	-20.9%	-15.9%	-4.1%	-20.9%
Skew	3.4	1.4	1.1	1.3	1.2	-0.5	2.4	0.3	-0.5	-0.4	-0.5	-1.1	0.0	2.8	-1.8
Kurtosis	35.1	30.0	31.1	30.8	31.3	32.7	16.6	15.8	17.7	16.9	17.9	18.5	17.0	20.2	22.1
Panel C: 1m-Mom															
monthly				bimonthly				quarterly							
Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log
Mean	0.2%	0.3%	0.8%	1.0%	0.9%	1.1%	0.0%	0.3%	0.7%	0.8%	0.8%	0.9%	0.9%	0.0%	0.3%
Std	2.7%	2.7%	2.6%	2.5%	2.5%	2.5%	1.9%	1.9%	1.8%	1.7%	1.7%	1.7%	1.7%	1.7%	1.6%
Min	-14.7%	-14.7%	-14.7%	-14.7%	-28.5%	-28.5%	-7.2%	-9.6%	-9.6%	-9.6%	-9.6%	-9.6%	-9.6%	-7.2%	-14.9%
Skew	0.9	0.0	0.1	0.0	0.0	-0.7	0.6	-0.4	-0.4	-0.5	-0.4	-0.5	-0.5	1.7	-1.6
Kurtosis	4.7	5.1	6.0	6.8	6.5	8.6	2.3	2.7	4.0	4.5	4.2	4.9	4.7	9.4	11.3
Panel D: 3m-Mom															
monthly				bimonthly				quarterly							
Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log
Mean	0.2%	0.2%	0.7%	0.9%	1.0%	1.1%	0.0%	0.2%	0.6%	0.7%	0.7%	0.7%	0.7%	0.0%	0.2%
Std	2.6%	2.6%	2.5%	2.4%	2.4%	2.4%	2.0%	1.7%	1.6%	1.5%	1.5%	1.5%	1.5%	1.7%	1.6%
Min	-8.4%	-28.4%	-28.4%	-28.4%	-28.4%	-28.4%	-6.5%	-16.9%	-16.9%	-16.9%	-16.9%	-16.9%	-16.9%	-5.5%	-15.7%
Skew	1.2	-0.2	-0.3	-0.6	-0.4	-0.3	1.6	-1.6	-1.6	-1.5	-1.2	-1.3	-1.3	2.1	-1.9
Kurtosis	6.4	6.8	8.3	9.9	9.0	9.9	7.9	8.2	12.4	13.9	12.9	14.1	14.1	11.0	12.5
Panel E: 12m-Mom															
monthly				bimonthly				quarterly							
Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log
Mean	0.3%	0.1%	0.5%	0.6%	0.8%	0.7%	0.3%	0.0%	0.4%	0.4%	0.4%	0.4%	0.5%	0.3%	0.0%
Std	2.4%	2.4%	2.3%	2.4%	2.3%	2.3%	1.8%	1.9%	1.8%	1.8%	1.8%	1.8%	1.8%	1.5%	1.6%
Min	-6.7%	-22.2%	-22.2%	-22.2%	-22.2%	-29.8%	-4.8%	-16.4%	-16.4%	-16.4%	-16.4%	-16.4%	-16.4%	-3.7%	-13.8%
Skew	2.1	-0.6	-0.6	-0.7	-0.8	-1.7	2.4	-2.0	-2.0	-2.3	-2.3	-2.4	-2.3	2.7	-2.5
Kurtosis	12.8	13.6	15.2	16.8	16.3	18.0	12.9	13.5	17.3	17.6	17.9	19.0	18.7	14.5	15.4

Table A1.S-1: Summary statistics of timed factors for portfolios with only short positions (monthly).

Panel A: Value														
	monthly					bimonthly					quarterly			
	Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF	RNN	LSTM
Sharpe	0.20	0.13	0.30	0.37	0.34	0.43	0.43	0.23	0.17	0.34	0.37	0.38	0.41	0.42
Sortino	0.44	0.16	0.33	0.37	0.36	0.40	0.40	0.57	0.18	0.30	0.33	0.33	0.35	0.35
$q(0.001)$	-6.3%	-17.3%	-17.3%	-17.3%	-17.3%	-17.3%	-17.3%	-5.0%	-12.1%	-12.1%	-12.1%	-12.1%	-12.1%	-12.1%
$q(0.01)$	-3.8%	-5.2%	-5.1%	-5.1%	-5.0%	-4.9%	-4.9%	-2.5%	-6.5%	-6.5%	-5.8%	-6.5%	-6.1%	-6.1%
$q(0.1)$	-1.8%	-2.1%	-1.4%	-1.2%	-1.2%	-0.9%	-0.9%	-1.3%	-1.3%	-0.7%	-0.7%	-0.7%	-0.5%	-0.5%
Panel B: Carry														
	monthly					bimonthly					quarterly			
	Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF	RNN	LSTM
Sharpe	0.41	0.11	0.18	0.17	0.20	0.20	0.18	0.39	0.15	0.25	0.20	0.26	0.31	0.30
Sortino	0.96	0.15	0.22	0.22	0.24	0.22	0.21	0.91	0.19	0.27	0.23	0.28	0.29	0.26
$q(0.001)$	-6.4%	-13.5%	-14.9%	-13.5%	-14.9%	-15.2%	-15.2%	-3.7%	-10.5%	-15.2%	-15.2%	-15.2%	-15.4%	-11.3%
$q(0.01)$	-3.9%	-9.0%	-9.1%	-9.0%	-9.1%	-9.1%	-9.1%	-2.8%	-5.4%	-5.5%	-5.7%	-5.5%	-4.9%	-5.3%
$q(0.1)$	-1.5%	-2.3%	-2.0%	-2.1%	-2.0%	-2.0%	-2.0%	-1.2%	-1.8%	-1.5%	-1.7%	-1.5%	-1.4%	-1.6%
Panel C: 1m-Mom														
	monthly					bimonthly					quarterly			
	Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF	RNN	LSTM
Sharpe	0.08	0.11	0.32	0.40	0.37	0.45	0.40	0.01	0.15	0.42	0.47	0.44	0.52	0.50
Sortino	0.14	0.15	0.44	0.52	0.49	0.52	0.48	0.02	0.20	0.52	0.56	0.54	0.60	0.58
$q(0.001)$	-8.1%	-12.4%	-11.8%	-11.8%	-12.2%	-12.2%	-12.5%	-6.3%	-8.9%	-8.9%	-8.9%	-8.9%	-8.9%	-8.9%
$q(0.01)$	-5.5%	-7.2%	-6.5%	-6.5%	-6.3%	-6.2%	-6.3%	-4.5%	-5.4%	-4.6%	-4.6%	-4.7%	-4.5%	-4.4%
$q(0.1)$	-2.8%	-2.8%	-1.9%	-1.6%	-1.7%	-1.3%	-1.6%	-2.1%	-1.9%	-1.1%	-0.9%	-1.1%	-0.8%	-0.9%
Panel D: 3m-Mom														
	monthly					bimonthly					quarterly			
	Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF	RNN	LSTM
Sharpe	0.09	0.07	0.30	0.40	0.35	0.42	0.44	0.01	0.04	0.36	0.44	0.41	0.46	0.44
Sortino	0.17	0.09	0.40	0.48	0.44	0.52	0.54	0.02	0.04	0.35	0.41	0.42	0.43	0.43
$q(0.001)$	-7.2%	-11.6%	-11.8%	-11.9%	-11.6%	-11.6%	-11.6%	-5.9%	-13.0%	-12.9%	-12.9%	-12.9%	-12.9%	-12.9%
$q(0.01)$	-5.5%	-6.7%	-5.8%	-6.0%	-6.1%	-5.7%	-5.8%	-3.8%	-6.7%	-6.2%	-5.7%	-5.6%	-5.6%	-5.4%
$q(0.1)$	-2.6%	-2.8%	-2.0%	-1.5%	-1.8%	-1.5%	-1.4%	-2.1%	-2.0%	-1.1%	-0.9%	-1.0%	-0.9%	-0.9%
Panel E: 12m-Mom														
	monthly					bimonthly					quarterly			
	Factor	Log	KNN	SVM	RF	RNN	LSTM	Factor	Log	KNN	SVM	RF	RNN	LSTM
Sharpe	0.13	0.03	0.21	0.30	0.27	0.34	0.31	0.14	-0.02	0.25	0.24	0.25	0.29	0.32
Sortino	0.28	0.04	0.24	0.31	0.29	0.34	0.30	0.32	-0.02	0.22	0.21	0.22	0.24	0.24
$q(0.001)$	-5.5%	-14.5%	-14.5%	-14.5%	-14.5%	-14.5%	-17.4%	-4.2%	-12.6%	-12.6%	-13.0%	-13.0%	-13.0%	-13.0%
$q(0.01)$	-4.2%	-8.0%	-7.6%	-7.6%	-7.6%	-7.6%	-7.6%	-3.1%	-7.6%	-7.3%	-7.5%	-7.6%	-7.6%	-7.5%
$q(0.1)$	-2.2%	-2.3%	-1.7%	-1.3%	-1.5%	-1.1%	-1.3%	-1.6%	-1.8%	-1.1%	-1.1%	-1.1%	-0.9%	-1.0%

Table A1.S-2: Risk measures of timed factors for portfolios with only short positions (monthly).

Panel A: Value														
	monthly					bimonthly					quarterly			
	Dummy	Log	KNN	SVM	RF	RNN	LSTM	Dummy	Log	KNN	SVM	RF	RNN	LSTM
overall Accuracy	60%	60%	75%	83%	78%	88%	88%	61%	62%	81%	85%	83%	91%	89%
True Positives	60%	66%	77%	85%	82%	90%	89%	61%	69%	84%	88%	86%	92%	93%
True Negatives	0%	50%	70%	79%	73%	84%	85%	0%	52%	76%	81%	79%	81%	86%
Panel B: Carry														
	monthly					bimonthly					quarterly			
	Dummy	Log	KNN	SVM	RF	RNN	LSTM	Dummy	Log	KNN	SVM	RF	RNN	LSTM
overall Accuracy	67%	68%	76%	75%	77%	80%	77%	66%	73%	83%	80%	84%	85%	82%
True Positives	67%	71%	80%	78%	81%	83%	83%	66%	78%	85%	81%	87%	88%	86%
True Negatives	0%	56%	66%	67%	68%	71%	65%	0%	61%	77%	77%	79%	78%	74%
Panel C: 1m-Mom														
	monthly					bimonthly					quarterly			
	Dummy	Log	KNN	SVM	RF	RNN	LSTM	Dummy	Log	KNN	SVM	RF	RNN	LSTM
overall Accuracy	52%	55%	69%	76%	73%	80%	77%	51%	58%	76%	81%	79%	85%	81%
True Positives	52%	57%	70%	77%	75%	82%	80%	51%	58%	76%	82%	80%	86%	81%
True Negatives	0%	54%	68%	74%	72%	78%	75%	0%	57%	76%	80%	77%	83%	81%
Panel D: 3m-Mom														
	monthly					bimonthly					quarterly			
	Dummy	Log	KNN	SVM	RF	RNN	LSTM	Dummy	Log	KNN	SVM	RF	RNN	LSTM
overall Accuracy	51%	53%	70%	78%	74%	80%	81%	50%	52%	76%	82%	79%	84%	83%
True Positives	51%	55%	71%	78%	75%	82%	82%	50%	52%	76%	82%	79%	83%	83%
True Negatives	0%	52%	68%	77%	72%	78%	80%	0%	52%	76%	83%	78%	80%	82%
Panel E: 12m-Mom														
	monthly					bimonthly					quarterly			
	Dummy	Log	KNN	SVM	RF	RNN	LSTM	Dummy	Log	KNN	SVM	RF	RNN	LSTM
overall Accuracy	53%	56%	71%	78%	75%	83%	80%	54%	57%	78%	80%	80%	84%	89%
True Positives	53%	60%	72%	79%	76%	85%	83%	54%	64%	79%	81%	81%	85%	89%
True Negatives	0%	53%	69%	77%	73%	80%	78%	0%	52%	76%	78%	78%	82%	87%

Table A1.S-3: Accuracy of prediction for portfolios with only short positions.

Appendix 2: Currency Value Factor

Description: This appendix compares timed value factor portfolio returns to static value factor portfolio returns.

Table A2.1: Logistic Regression vs Value Factor

Table A2.2: KNN vs Value Factor

Table A2.3: SVM vs Value Factor

Table A2.4: RF vs Value Factor

Table A2.5: RNN vs Value Factor

Table A2.6: LSTM vs Value Factor

Appendix 2.1. Logistic Regression

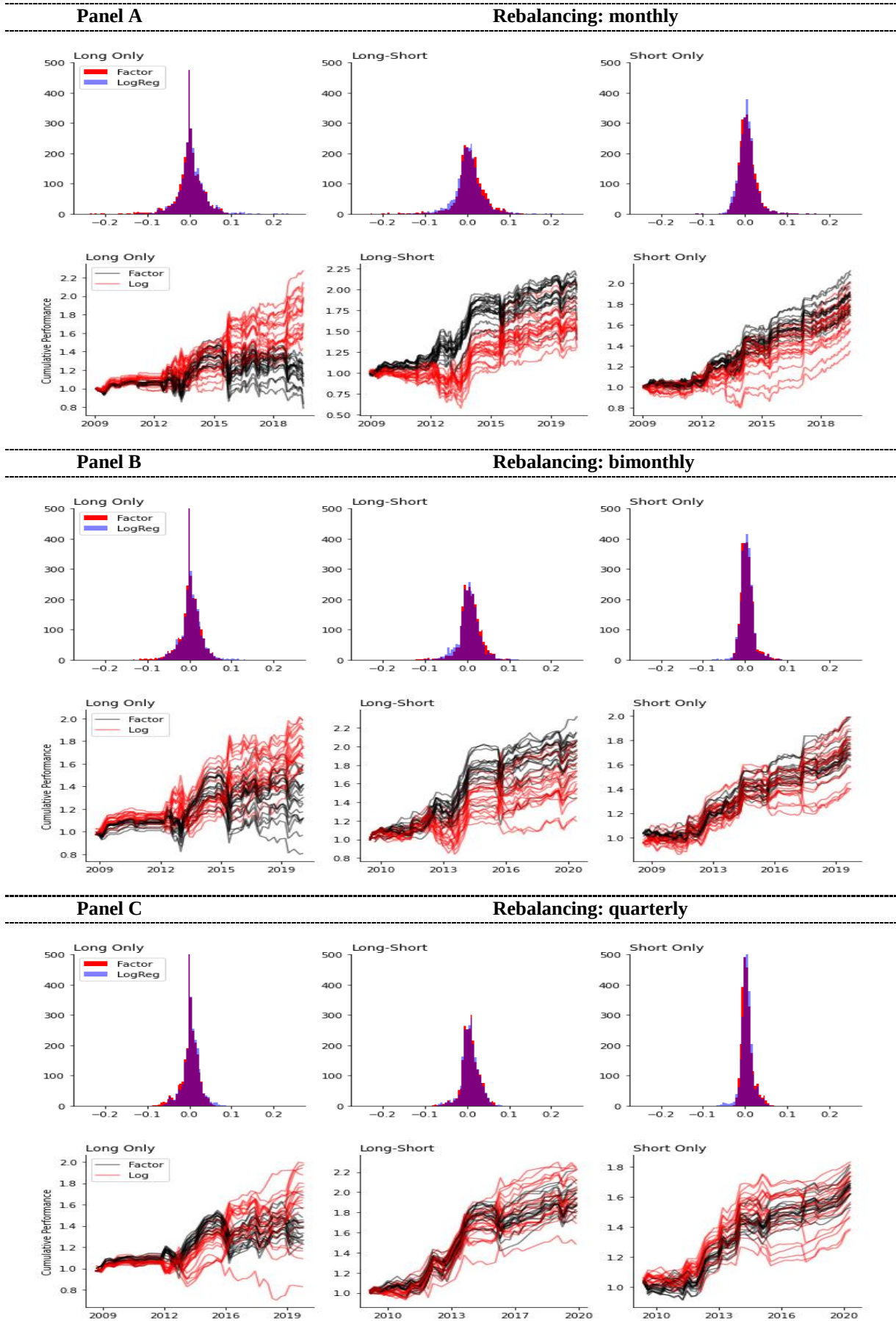


Table A2.1: Logistic Regression vs Value Factor.

The figures graphically compare (i) the distributions of the value factor with the distributions of the timed factor based on logistic regression and (ii) the performance over time of the same 20 portfolios with and without timing

Appendix 2.2. K-Nearest Neighbors (KNN)

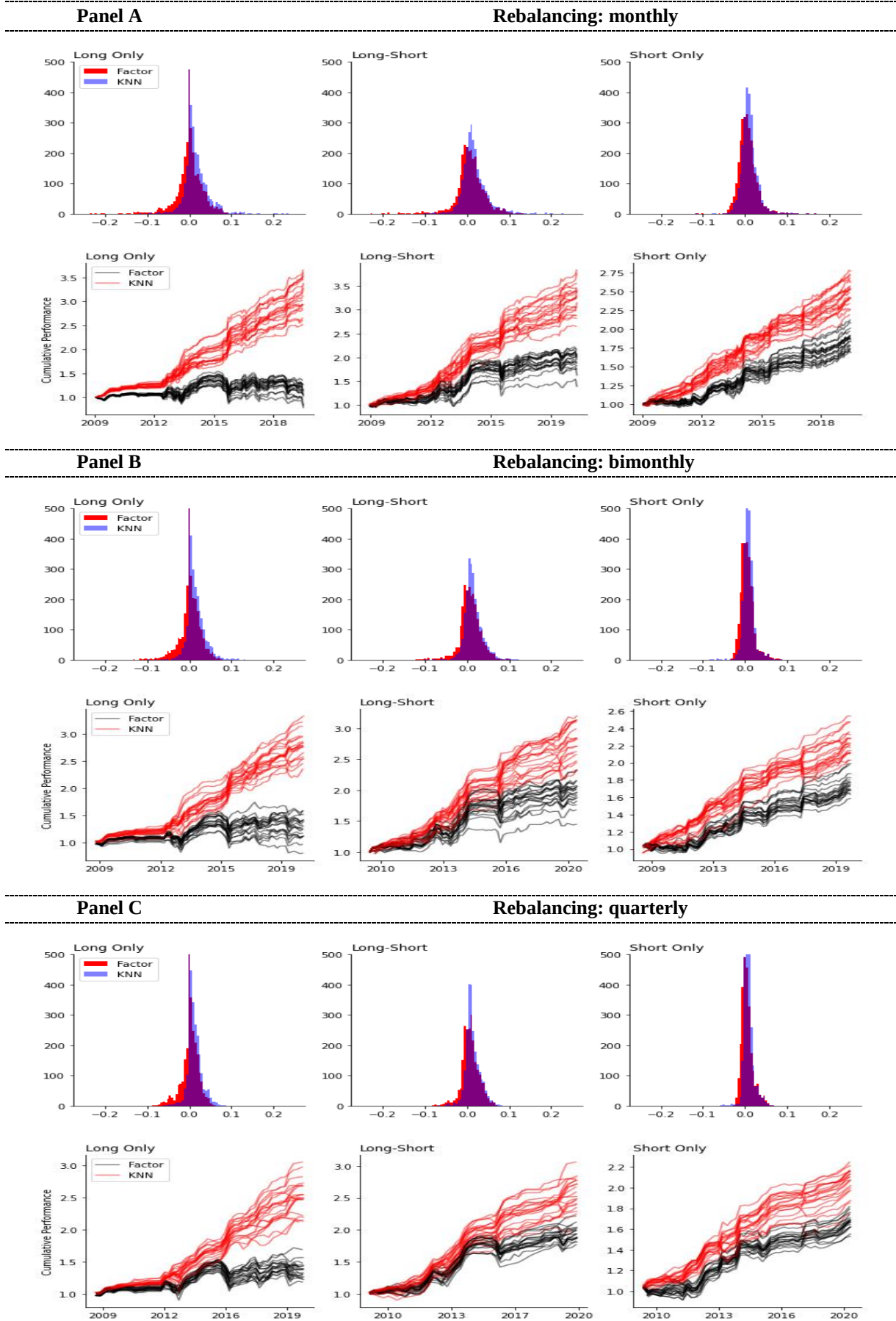


Table A2.2: KNN vs Value Factor.

The figures graphically compare (i) the distributions of the value factor with the distributions of the timed factor based on KNN and (ii) the performance over time of the same 20 portfolios with and without timing

Appendix 2.3. Support Vector Machine (SVM)

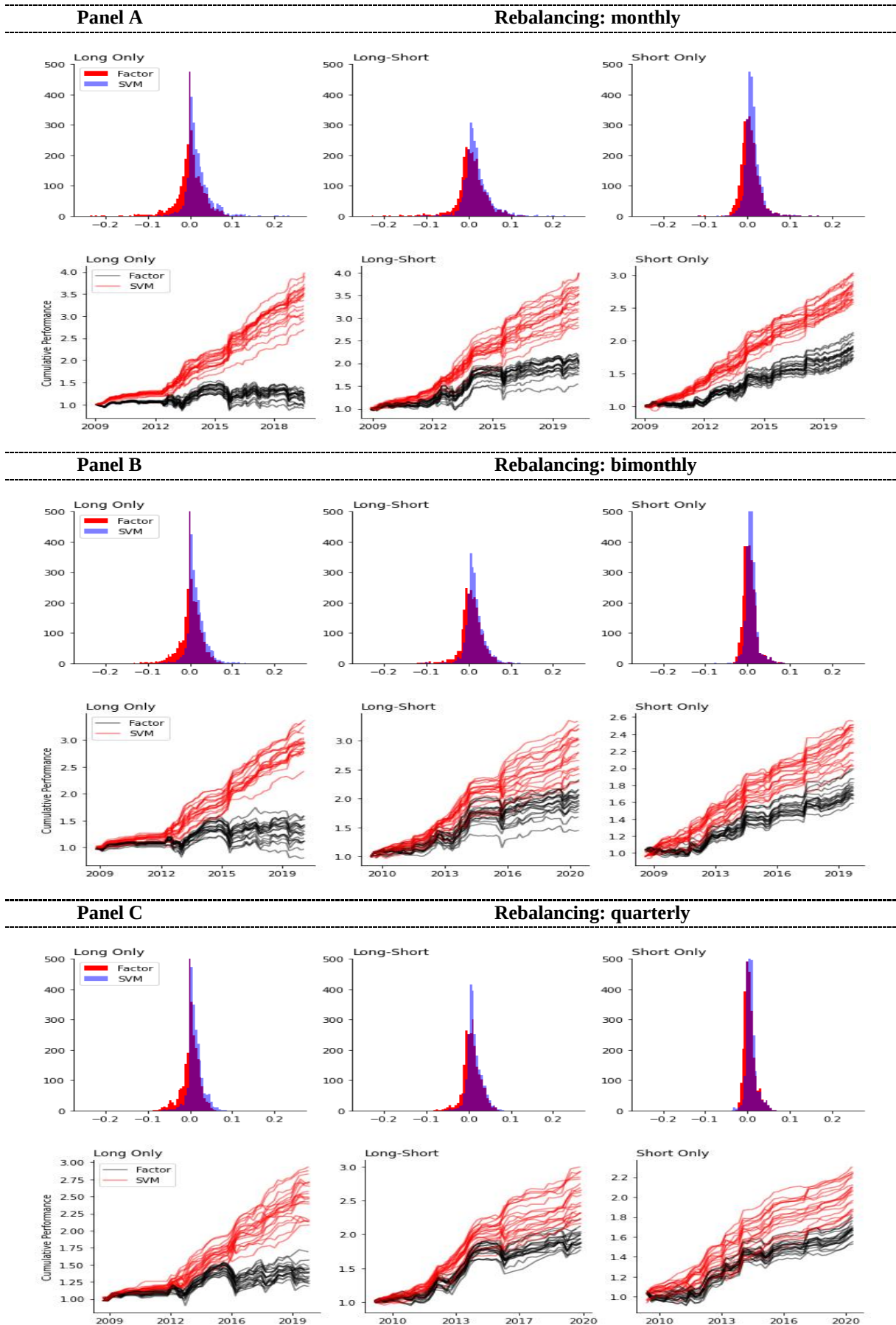


Table A2.3: SVM vs Value Factor.

The figures graphically compare (i) the distributions of the value factor with the distributions of the timed factor based on SVM and (ii) the performance over time of the same 20 portfolios with and without timing

Appendix 2.4. Random Forest (RF)

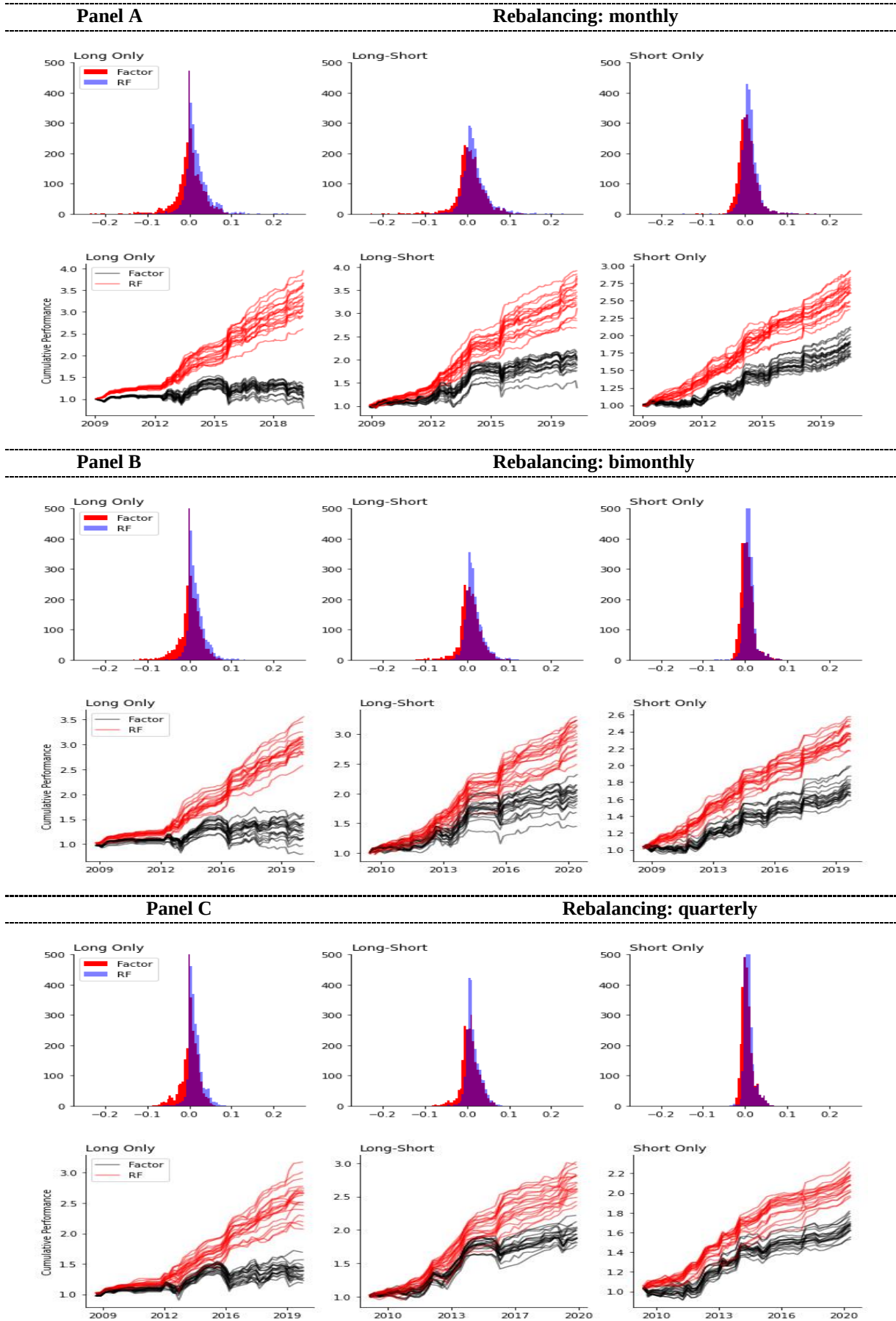


Table A2.4: RF vs Value Factor.

The figures graphically compare (i) the distributions of the value factor with the distributions of the timed factor based on RF and (ii) the performance over time of the same 20 portfolios with and without timing

Appendix 2.5. Recurrent Neural Network (RNN)

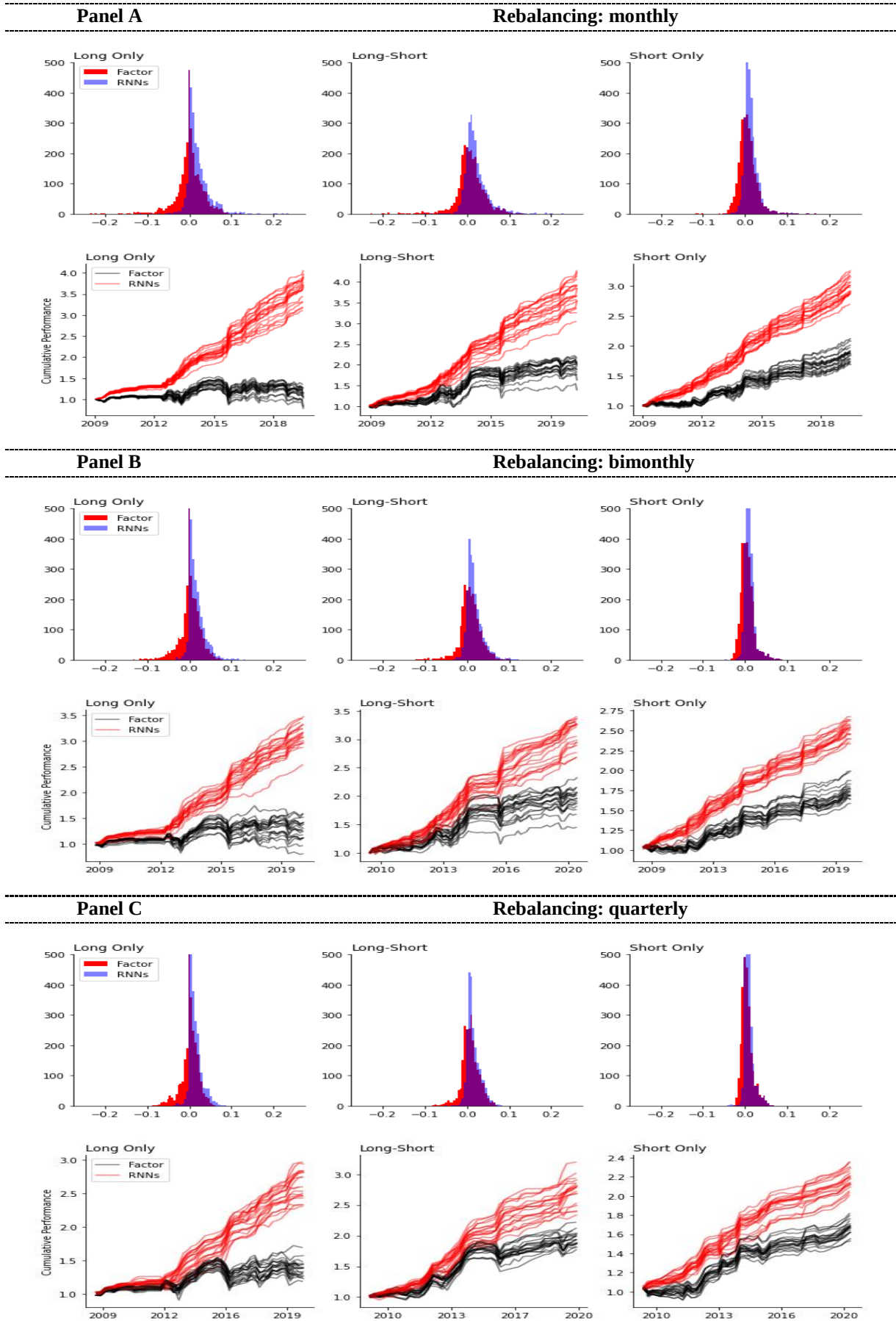


Table A2.5: RNN vs Value Factor.

The figures graphically compare (i) the distributions of the value factor with the distributions of the timed factor based on RNN and (ii) the performance over time of the same 20 portfolios with and without timing

Appendix 2.6. Long Short-Term Memory (LSTM)

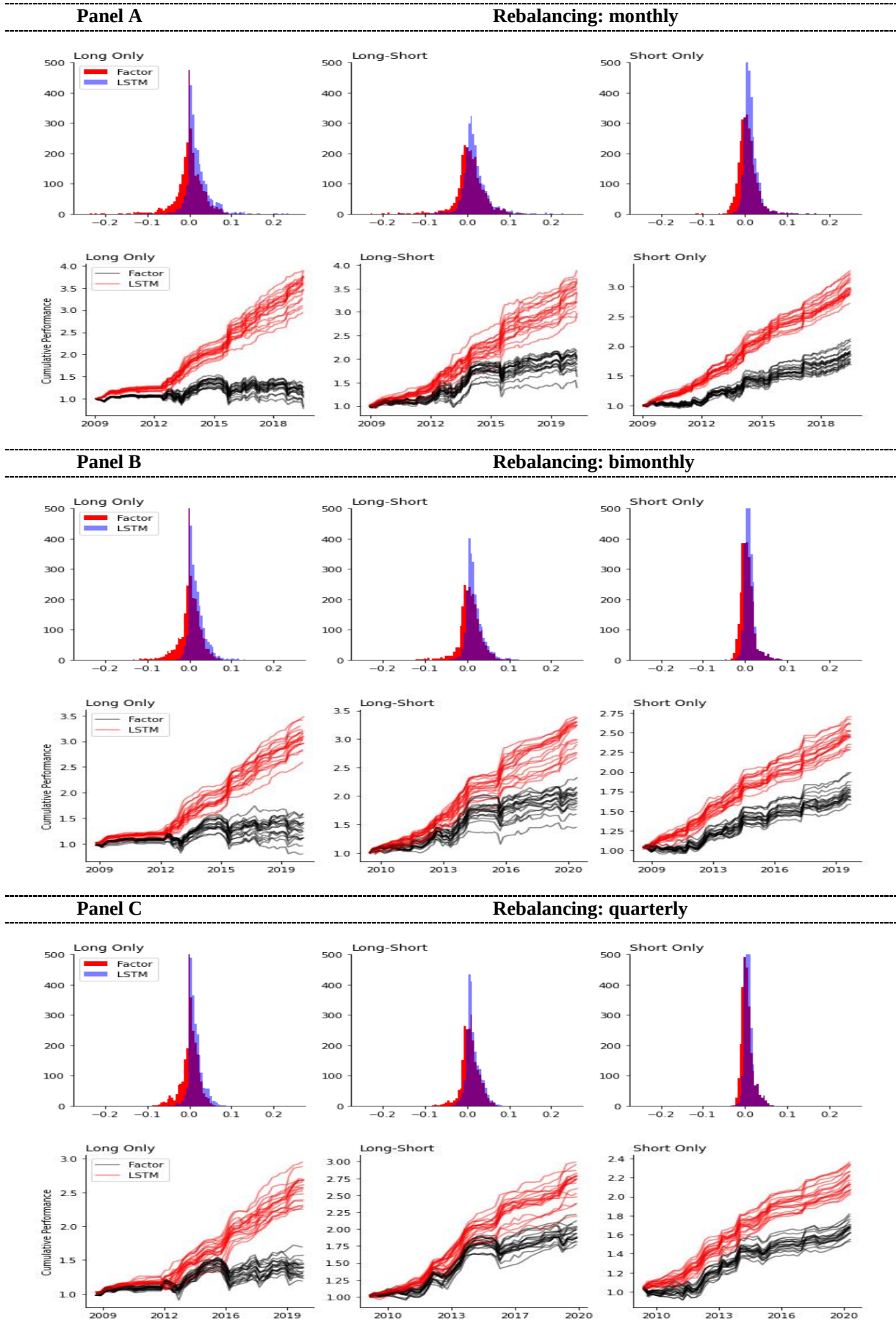


Table A2.6: LSTM vs Value Factor.

The figures graphically compare (i) the distributions of the value factor with the distributions of the timed factor based on LSTM and (ii) the performance over time of the same 20 portfolios with and without timing

Appendix 3: Currency Carry Factor

Description: This appendix compares timed carry factor portfolio returns to static carry factor portfolio returns.

Table A3.1: Logistic Regression vs Carry Factor

Table A3.2: KNN vs Carry Factor

Table A3.3: SVM vs Carry Factor

Table A3.4: RF vs Carry Factor

Table A3.5: RNN vs Carry Factor

Table A3.6: LSTM vs Carry Factor

Appendix 3.1. Logistic Regression

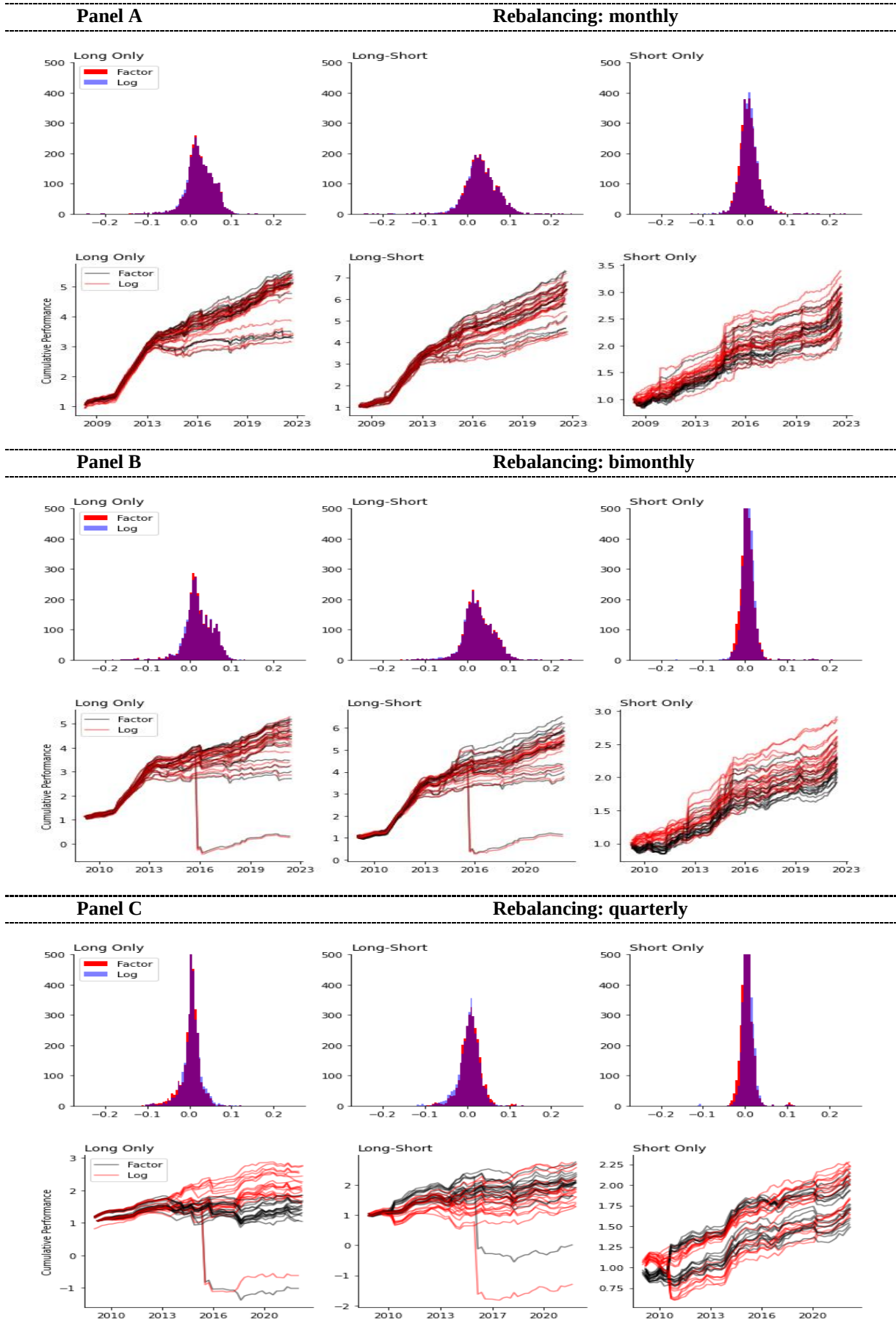


Table A3.1: Logistic Regression vs Carry Factor.

The figures graphically compare (i) the distributions of the carry factor with the distributions of the timed factor based on logistic regression and (ii) the performance over time of the same 20 portfolios with and without timing

Appendix 3.2. K-Nearest Neighbors (KNN)

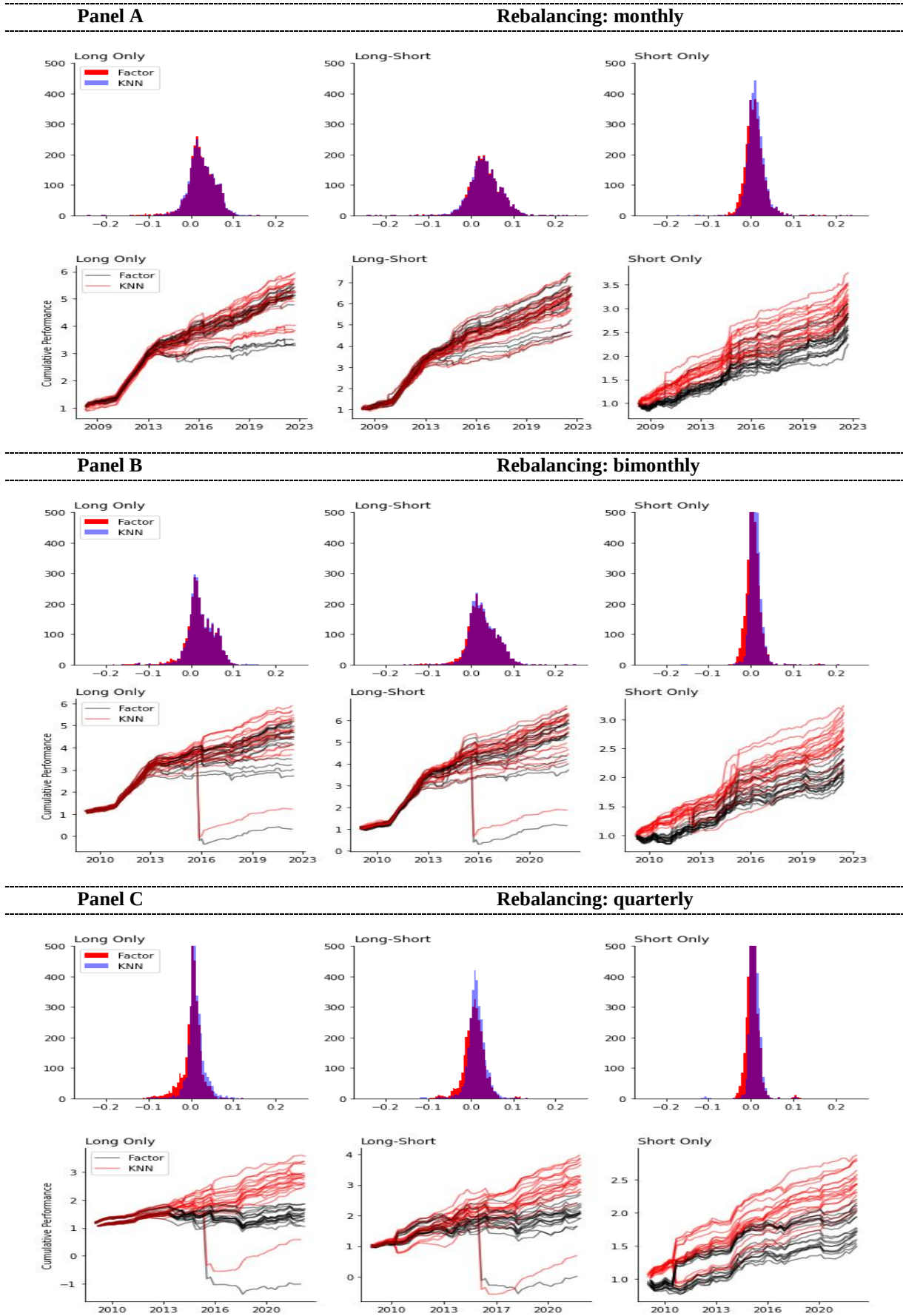


Table A3.2: KNN vs Carry Factor.

The figures graphically compare (i) the distributions of the carry factor with the distributions of the timed factor based on KNN and (ii) the performance over time of the same 20 portfolios with and without timing

Appendix 3.3. Support Vector Machine (SVM)

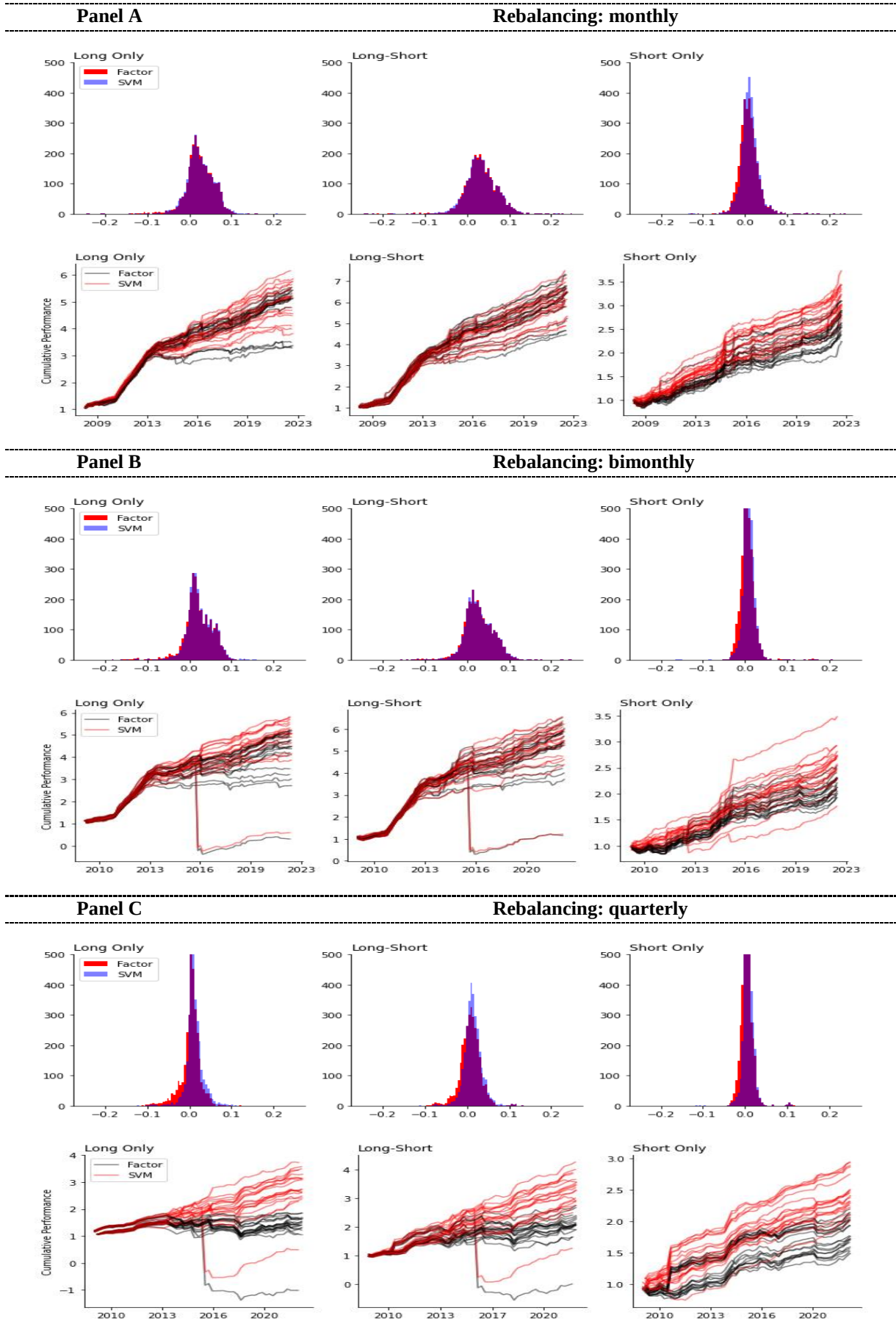


Table A3.3: SVM vs Carry Factor.

The figures graphically compare (i) the distributions of the carry factor with the distributions of the timed factor based on SVM and (ii) the performance over time of the same 20 portfolios with and without timing

Appendix 3.4. Random Forest (RF)

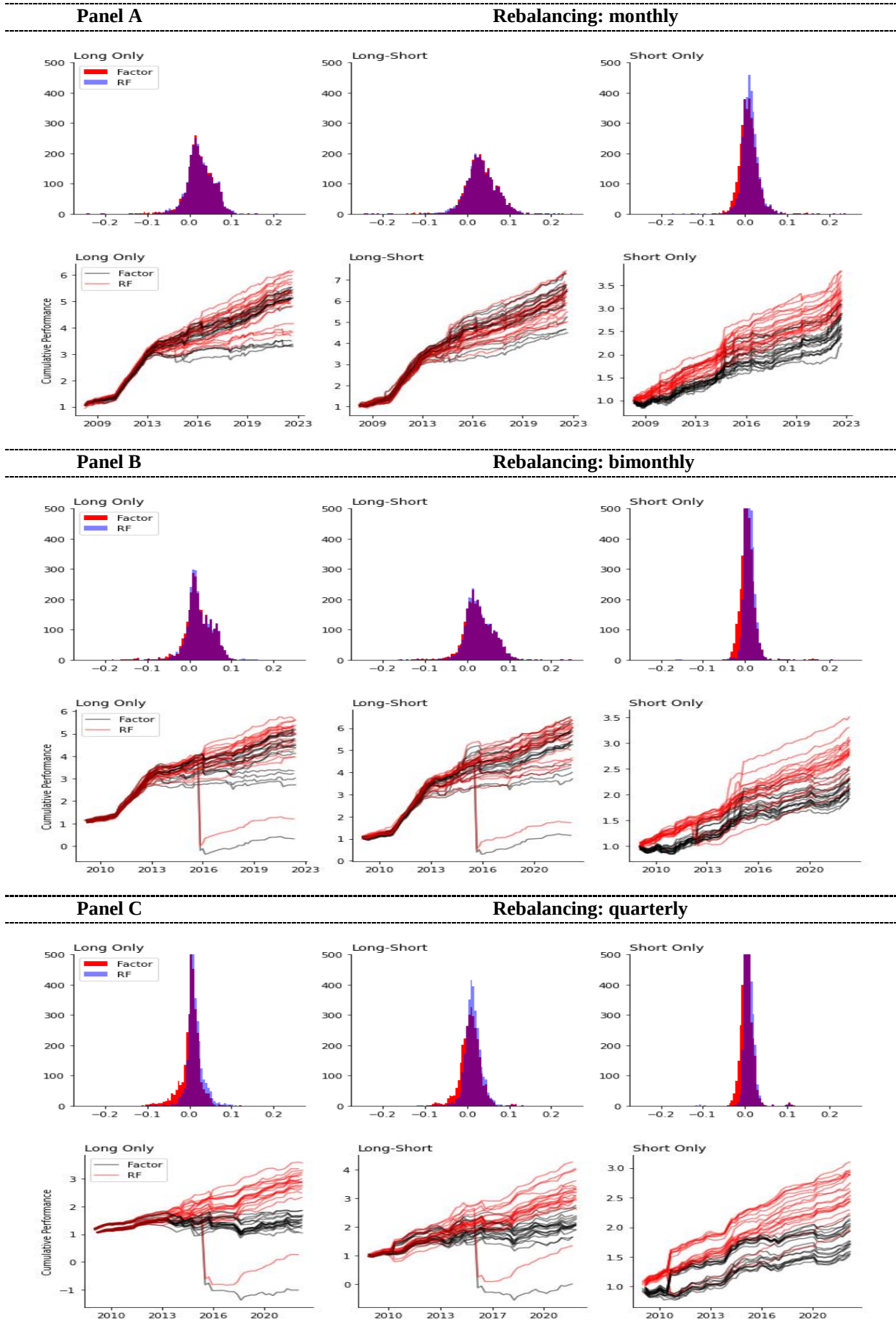


Table A3.4: RF vs Carry Factor.

The figures graphically compare (i) the distributions of the carry factor with the distributions of the timed factor based on RF and (ii) the performance over time of the same 20 portfolios with and without timing

Appendix 3.5. Recurrent Neural Network (RNN)

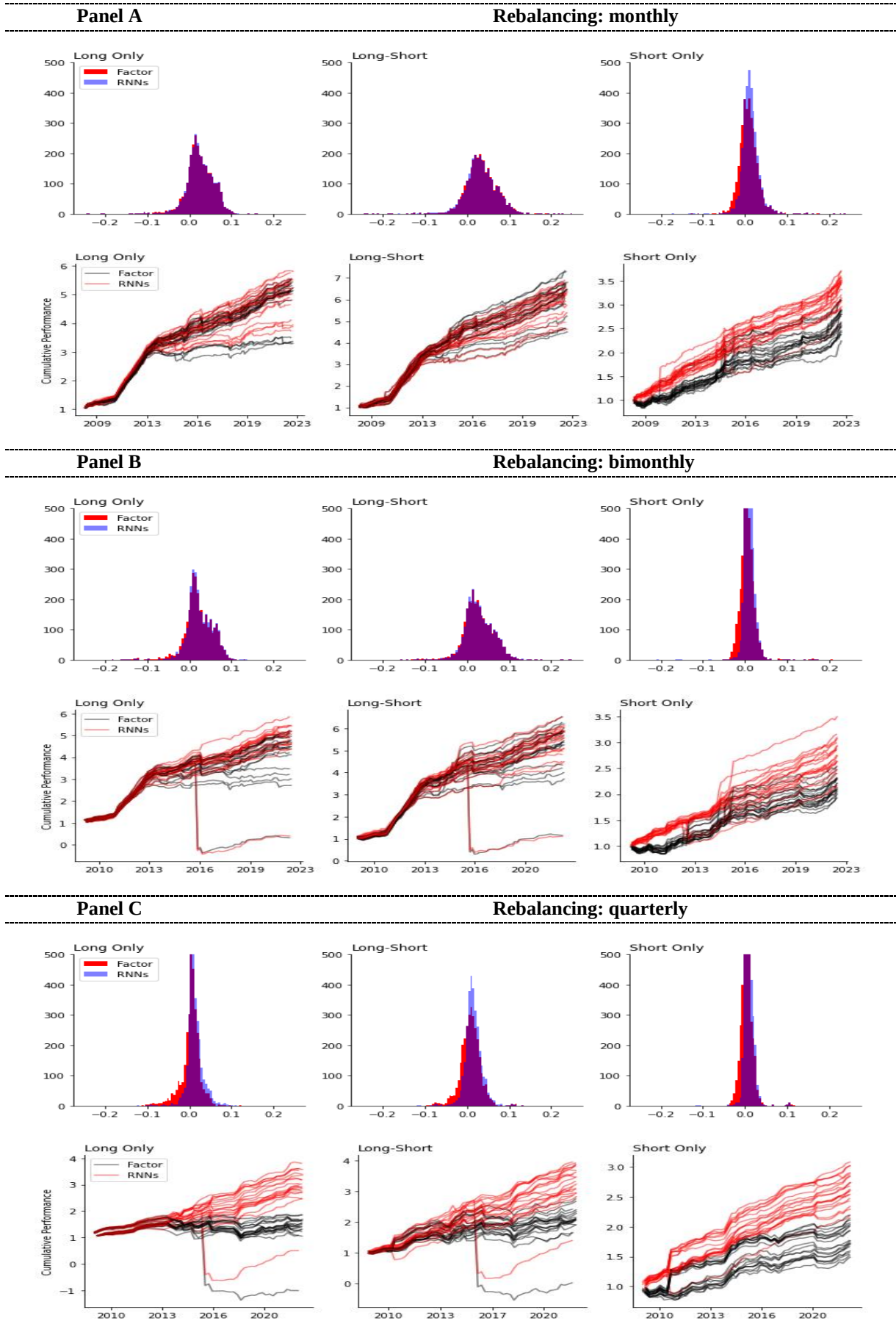


Table A3.5: RNN vs Carry Factor.

The figures graphically compare (i) the distributions of the carry factor with the distributions of the timed factor based on RNN and (ii) the performance over time of the same 20 portfolios with and without timing

Appendix 3.6. Long Short-Term Memory (LSTM)

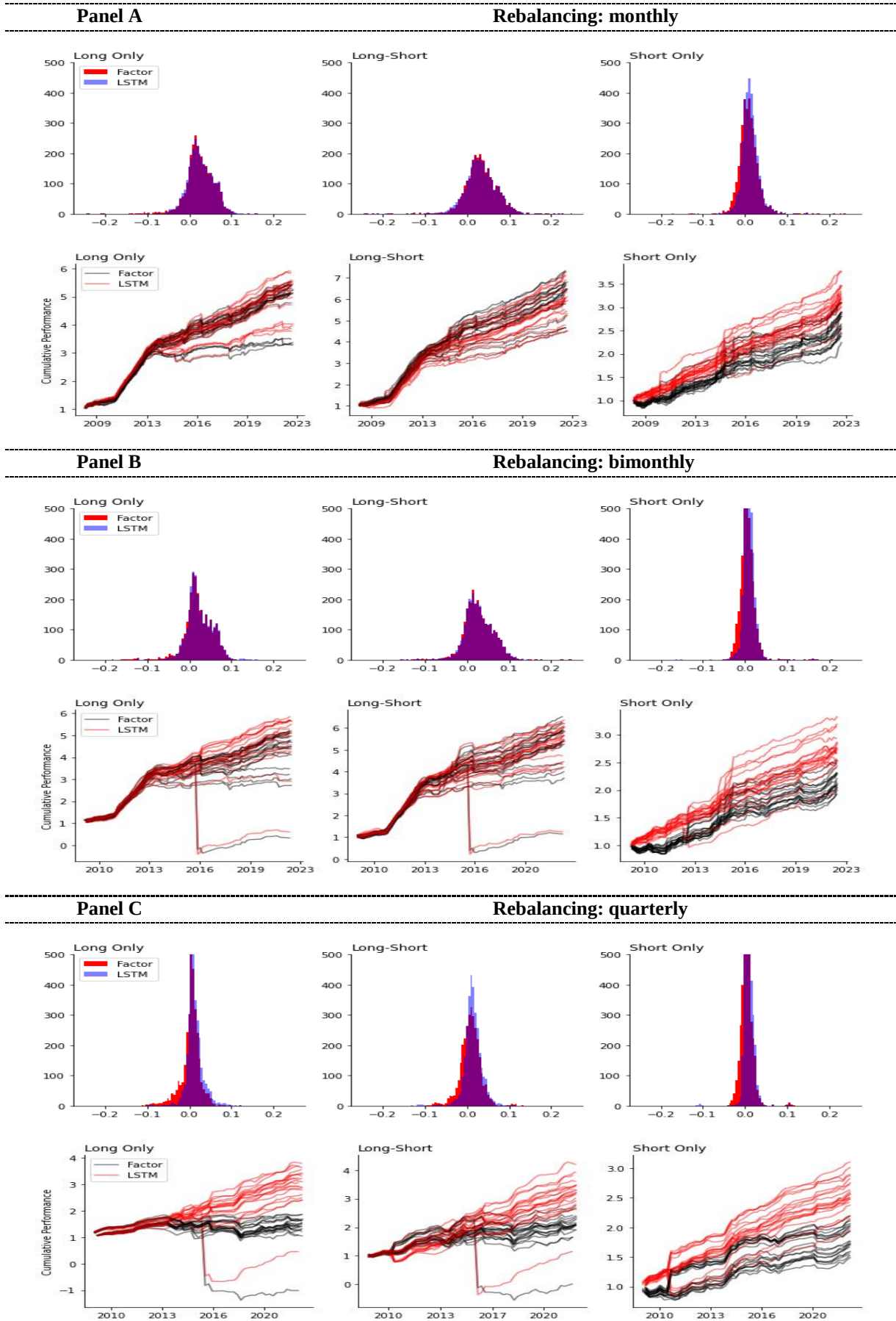


Table A3.6: LSTM vs Carry Factor.

The figures graphically compare (i) the distributions of the carry factor with the distributions of the timed factor based on LSTM and (ii) the performance over time of the same 20 portfolios with and without timing

Appendix 4: Currency Momentum Factor

Description: This appendix compares timed momentum factor portfolio returns to static momentum factor portfolio returns.

Table A4.M1-1: 1m-momentum Factor.

Table A4.M1-2: Logistic Regression vs 1m-momentum Factor.

Table A4.M1-3: KNN vs 1m-momentum Factor.

Table A4.M1-4: SVM vs 1m-momentum Factor.

Table A4.M1-5: RF vs 1m-momentum Factor.

Table A4.M1-6: RNN vs 1m-momentum Factor.

Table A4.M1-7: LSTM vs 1m-momentum Factor.

Table A4.M3-1: 3m-momentum Factor.

Table A4.M3-2: Logistic Regression vs 3m-momentum Factor.

Table A4.M3-3: KNN vs 3m-momentum Factor.

Table A4.M3-4: SVM vs 3m-momentum Factor.

Table A4.M3-5: RF vs 3m-momentum Factor.

Table A4.M3-6: RNN vs 3m-momentum Factor.

Table A4.M3-7: LSTM vs 3m-momentum Factor.

Table A4.M12-1: 12m-momentum Factor.

Table A4.M12-2: Logistic Regression vs 12m-momentum Factor.

Table A4.M12-3: KNN vs 12m-momentum Factor.

Table A4.M12-4: SVM vs 12m-momentum Factor.

Table A4.M12-5: RF vs 12m-momentum Factor.

Table A4.M12-6: RNN vs 12m-momentum Factor.

Table A4.M12-7: LSTM vs 12m-momentum Factor.

Appendix 4.M1.1. 1m-Momentum Factor

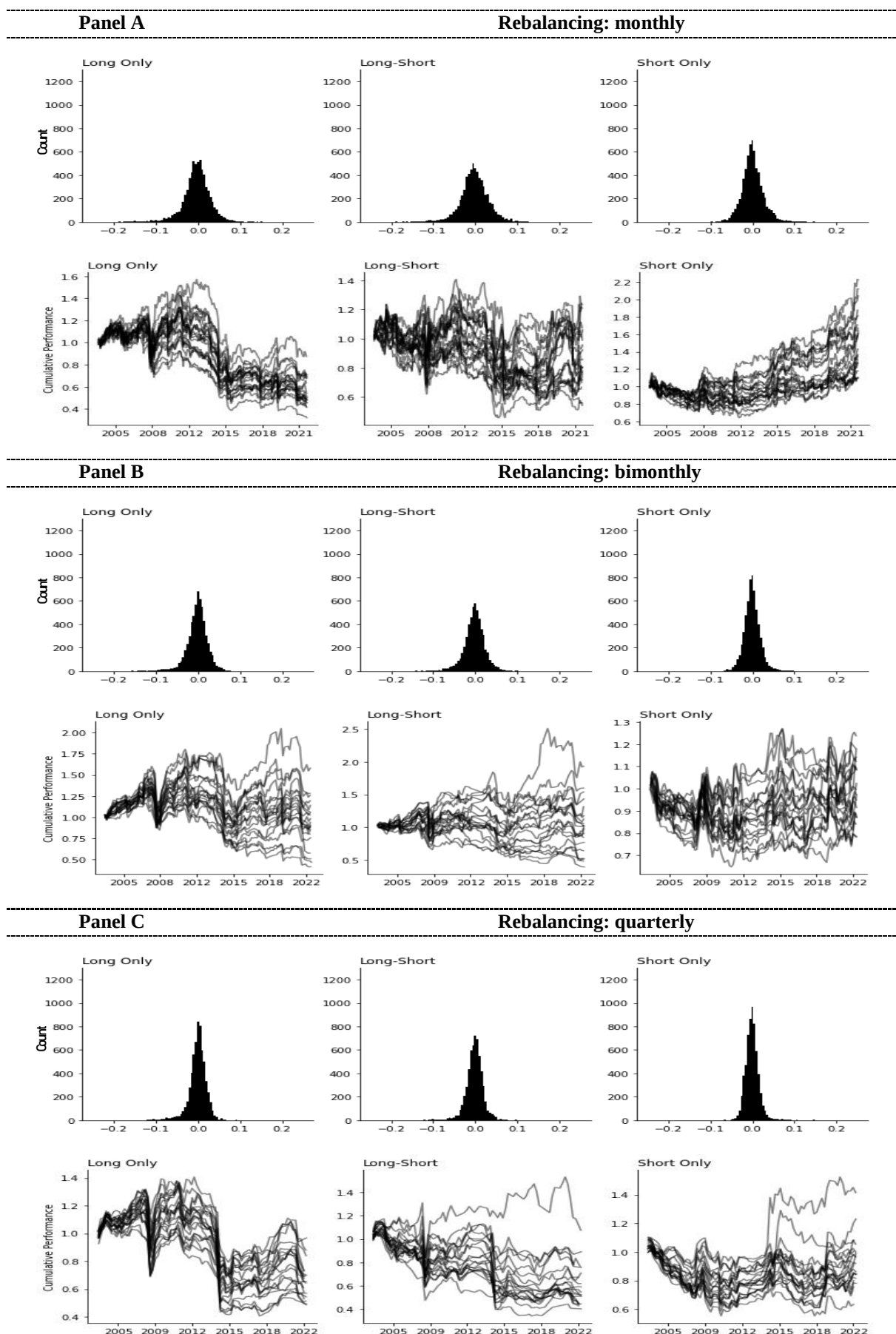


Table A4.M1-1: 1m-momentum Factor.

The figures graphically show (i) the distributions of the 1m-Momentum factor and (ii) the performance over time of 20 portfolios

Appendix 4.M1.2. Logistic Regression

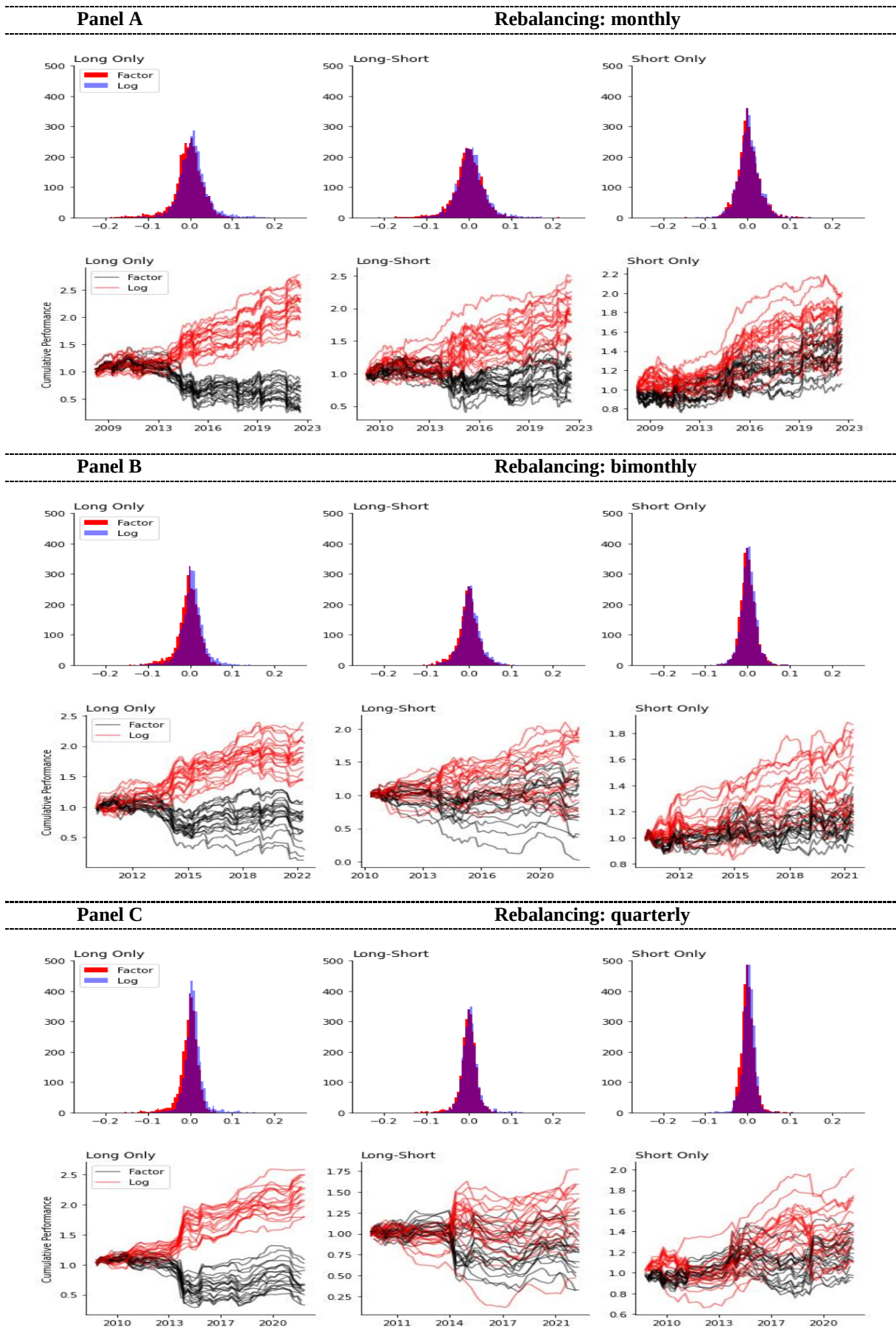


Table A4.M1-2: Logistic Regression vs 1m-momentum Factor.

The figures graphically compare (i) the distributions of the 1m-Momentum factor with the distributions of the timed factor based on logistic regression and (ii) the performance over time of the same 20 portfolios with and without timing

Appendix 4.M1.3. K-Nearest Neighbors (KNN)

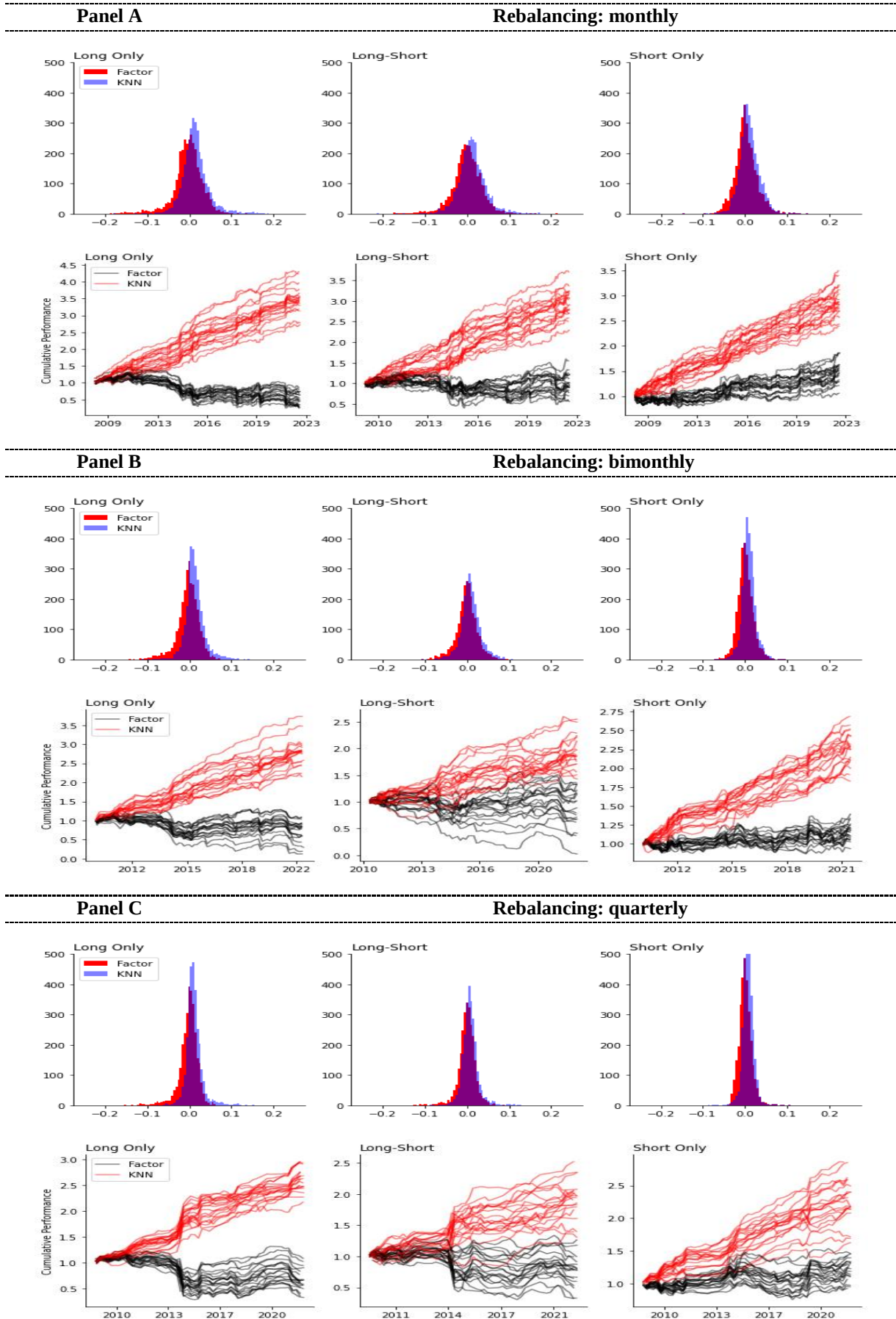


Table A4.M1-3: KNN vs 1m-momentum Factor.

The figures graphically compare (i) the distributions of the 1m-Momentum factor with the distributions of the timed factor based on KNN and (ii) the performance over time of the same 20 portfolios with and without timing

Appendix 4.M1.4. Support Vector Machine (SVM)

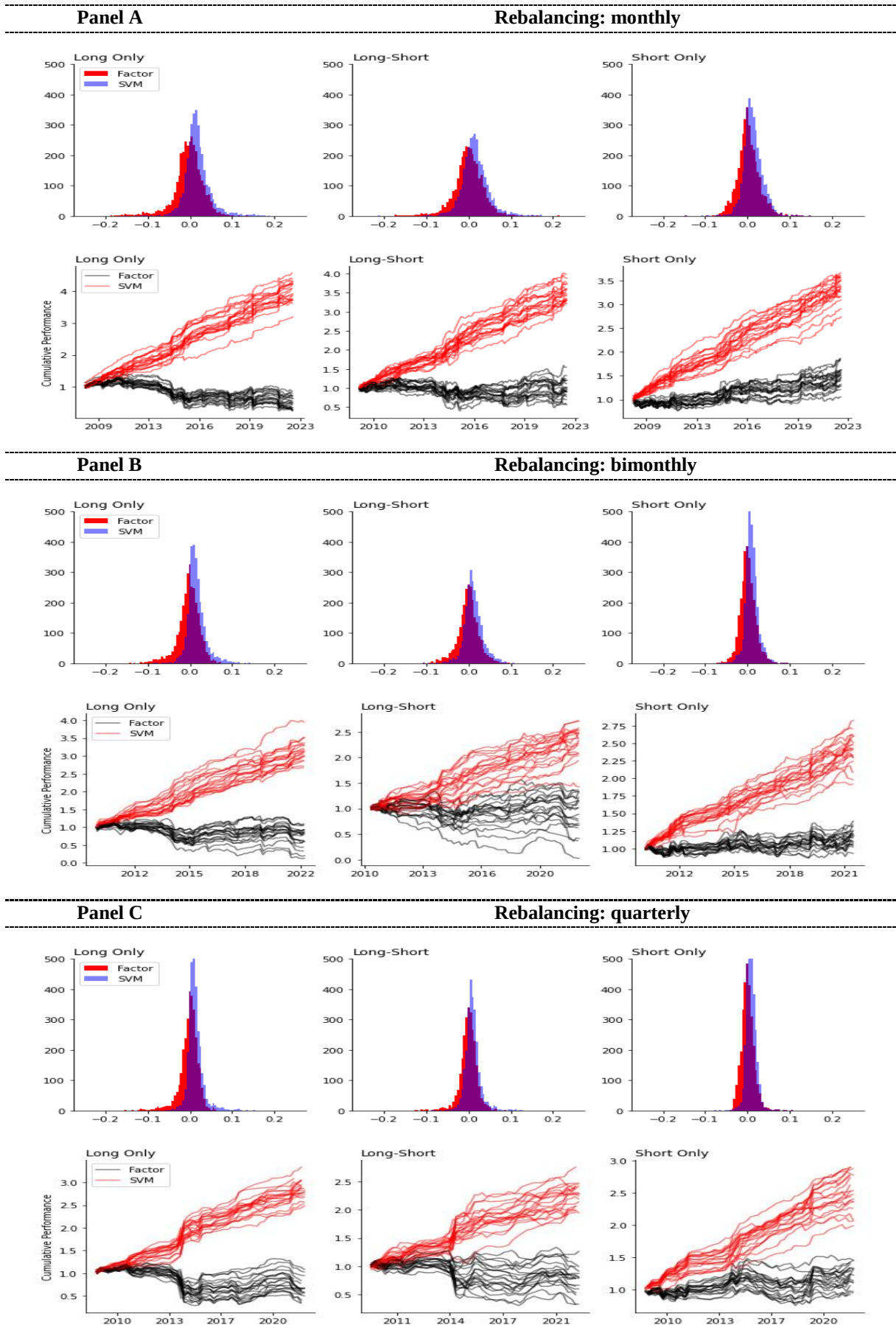


Table A4.M1-4: SVM vs 1m-momentum Factor.

The figures graphically compare (i) the distributions of the 1m-Momentum factor with the distributions of the timed factor based on SVM and (ii) the performance over time of the same 20 portfolios with and without timing

Appendix 4.M1.5. Random Forest (RF)

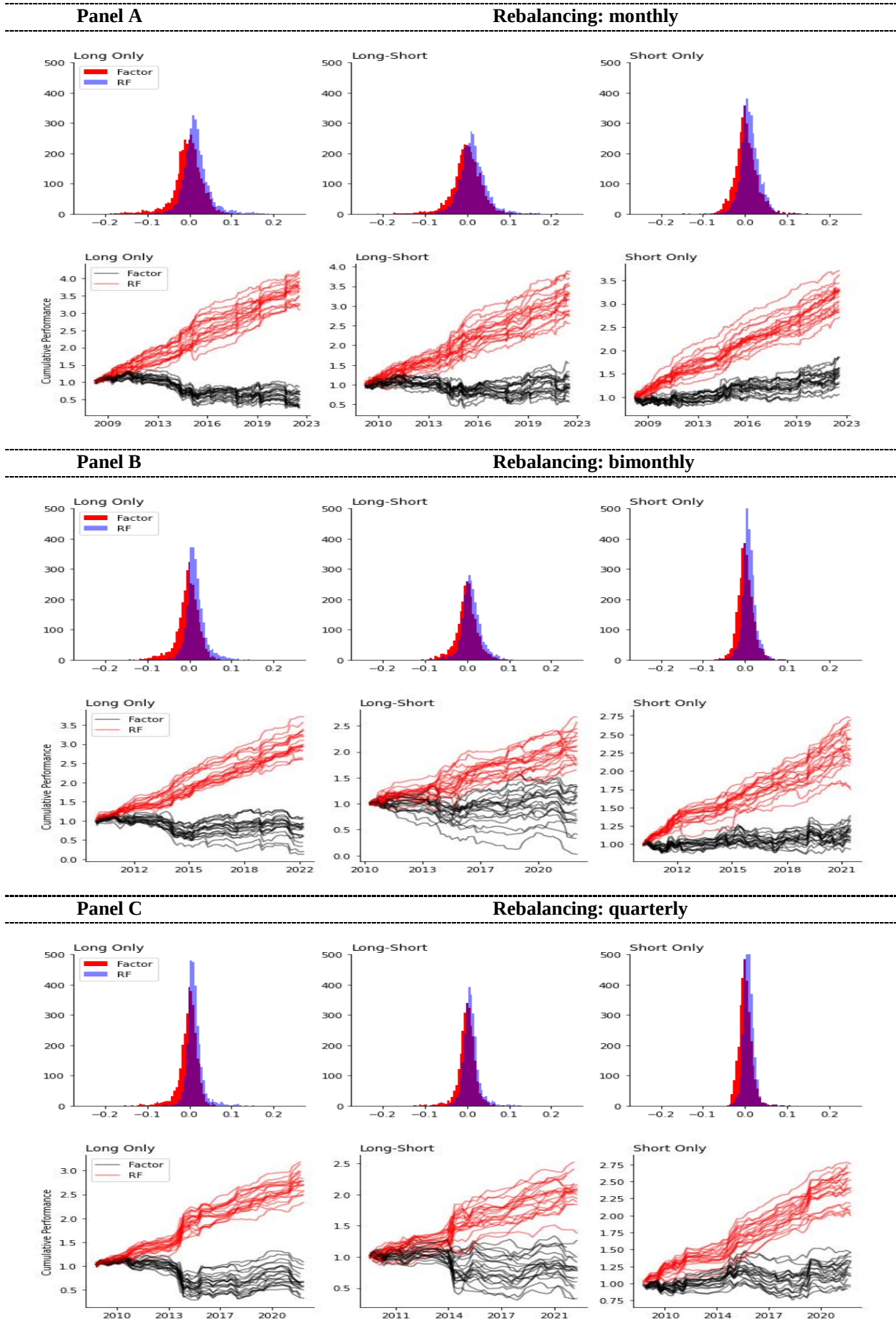


Table A4.M1-5: RF vs 1m-momentum Factor.

The figures graphically compare (i) the distributions of the 1m-Momentum factor with the distributions of the timed factor based on RF and (ii) the performance over time of the same 20 portfolios with and without timing

Appendix 4.M1.6. Recurrent Neural Network (RNN)

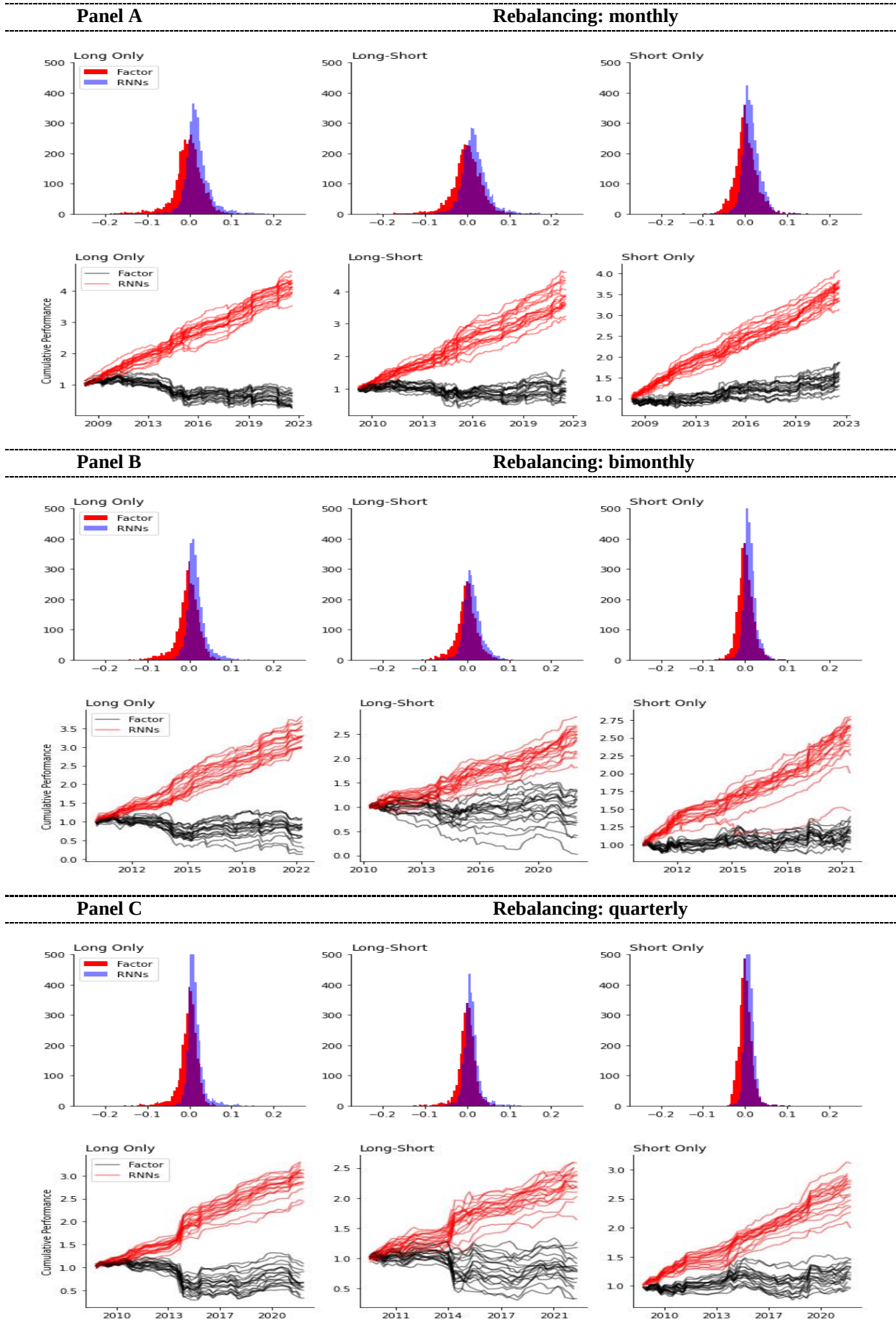


Table A4.M1-6: RNN vs 1m-momentum Factor.

The figures graphically compare (i) the distributions of the 1m-Momentum factor with the distributions of the timed factor based on RNN and (ii) the performance over time of the same 20 portfolios with and without timing

Appendix 4.M1.7. Long Short-Term Memory (LSTM)

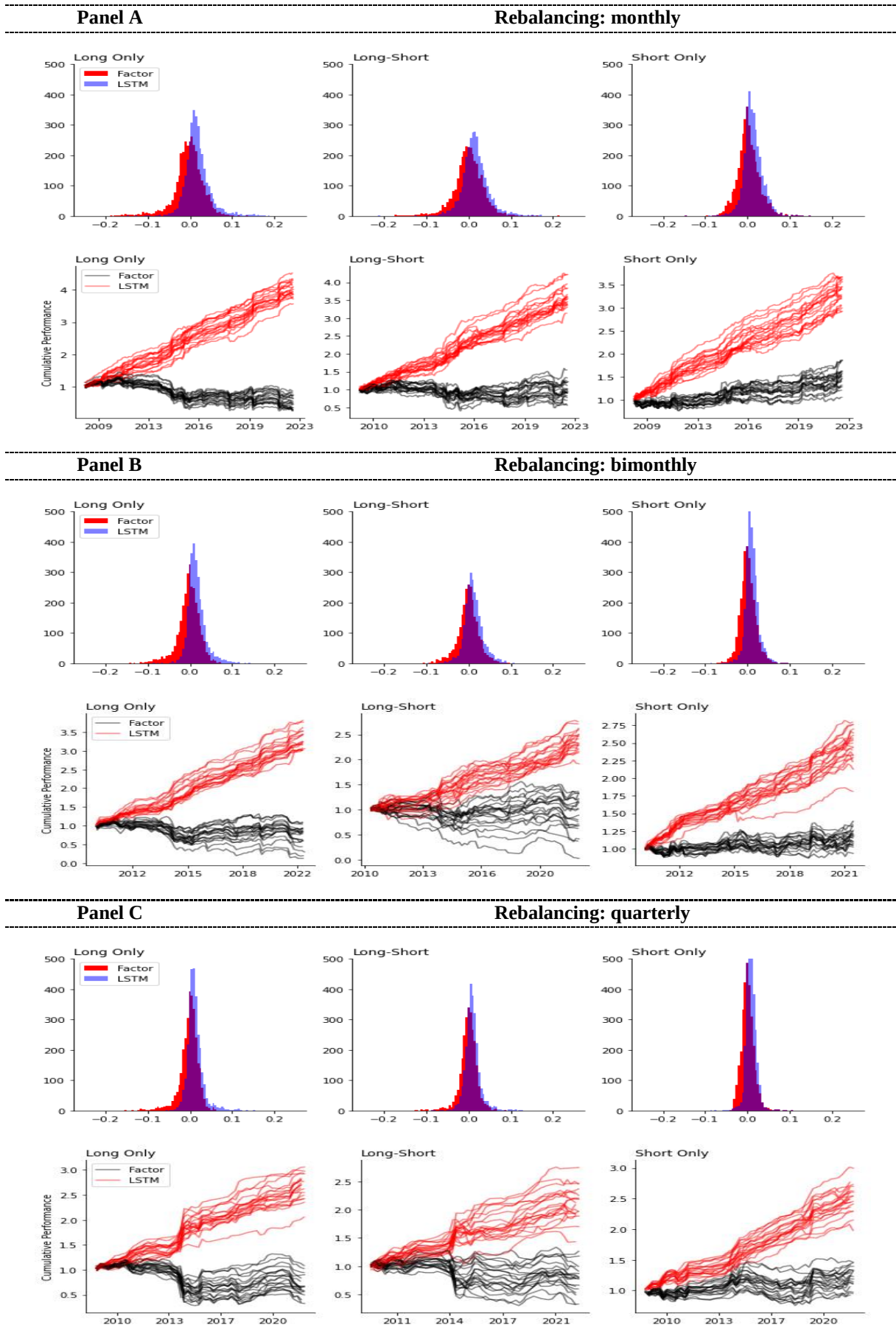


Table A4.M1-7: LSTM vs 1m-momentum Factor.

The figures graphically compare (i) the distributions of the 1m-Momentum factor with the distributions of the timed factor based on LSTM and (ii) the performance over time of the same 20 portfolios with and without timing

Appendix 4.M3.1. 3m-Momentum Factor

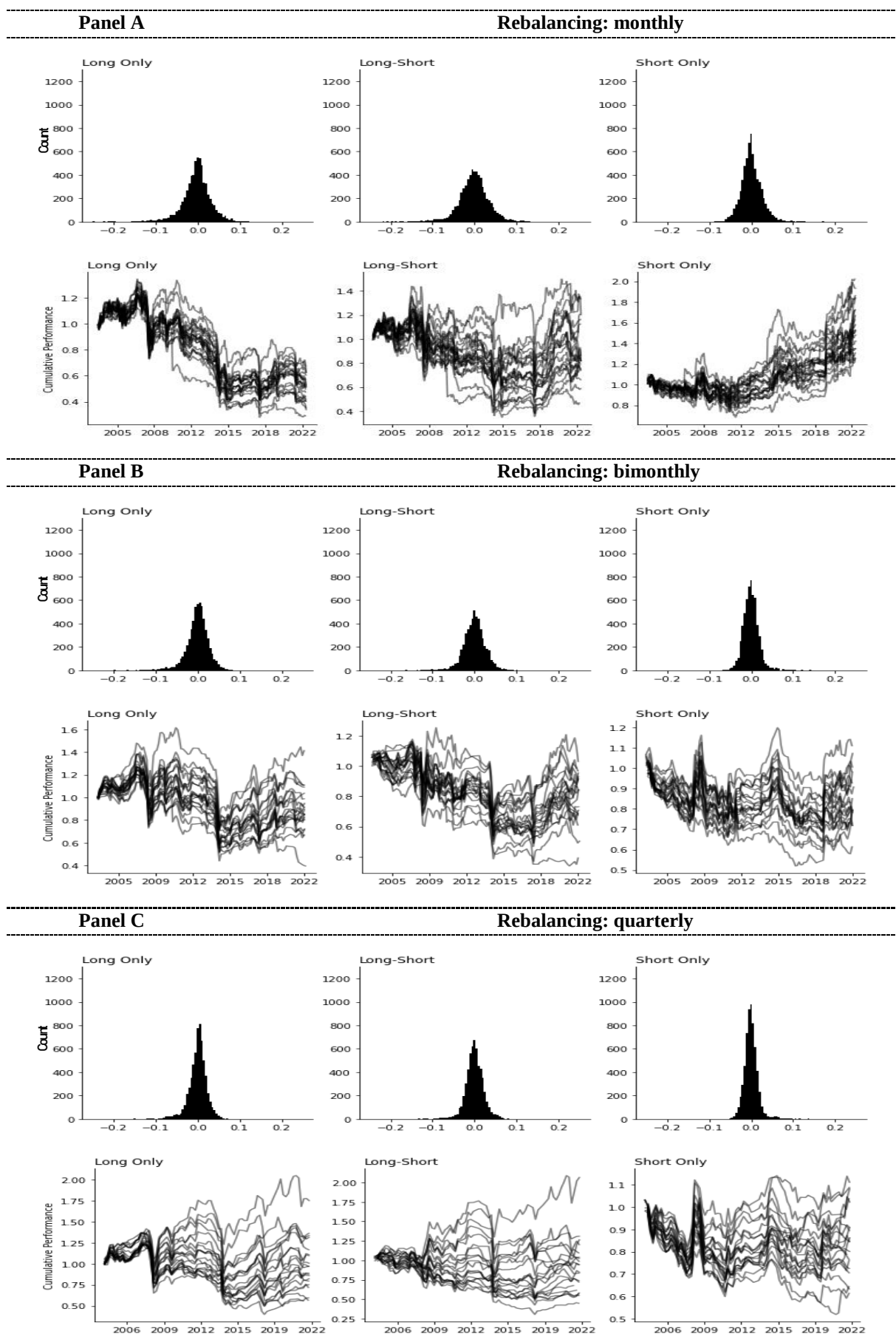


Table A4.M3-1: 3m-momentum Factor.

The figures graphically show (i) the distributions of the 3m-Momentum factor and (ii) the performance over time of 20 portfolios

Appendix 4.M3.2. Logistic Regression

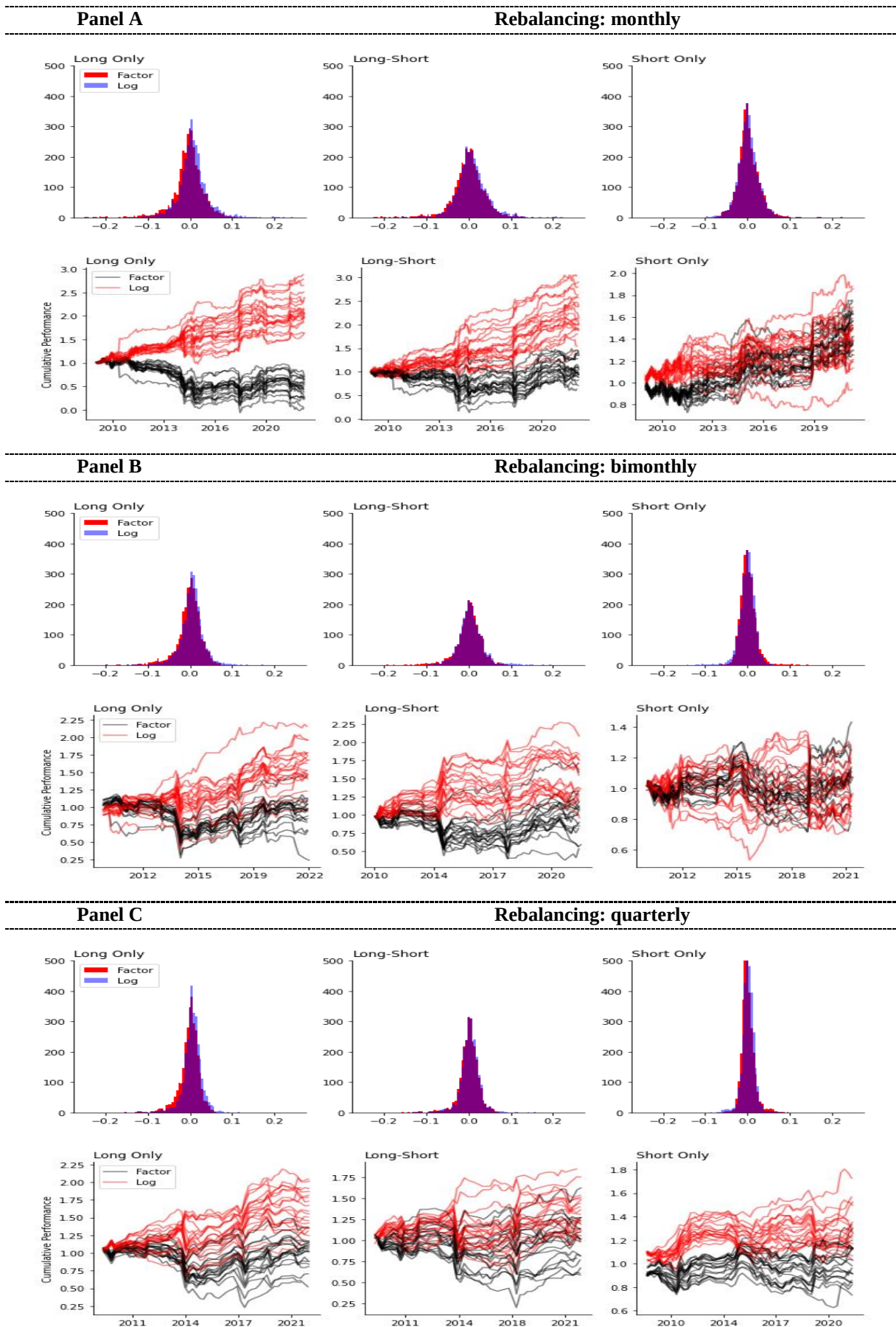


Table A4.M3-2: Logistic Regression vs 3m-momentum Factor.

The figures graphically compare (i) the distributions of the 3m-Momentum factor with the distributions of the timed factor based on logistic regression and (ii) the performance over time of the same 20 portfolios with and without timing

Appendix 4.M3.3 K-Nearest Neighbors (KNN)

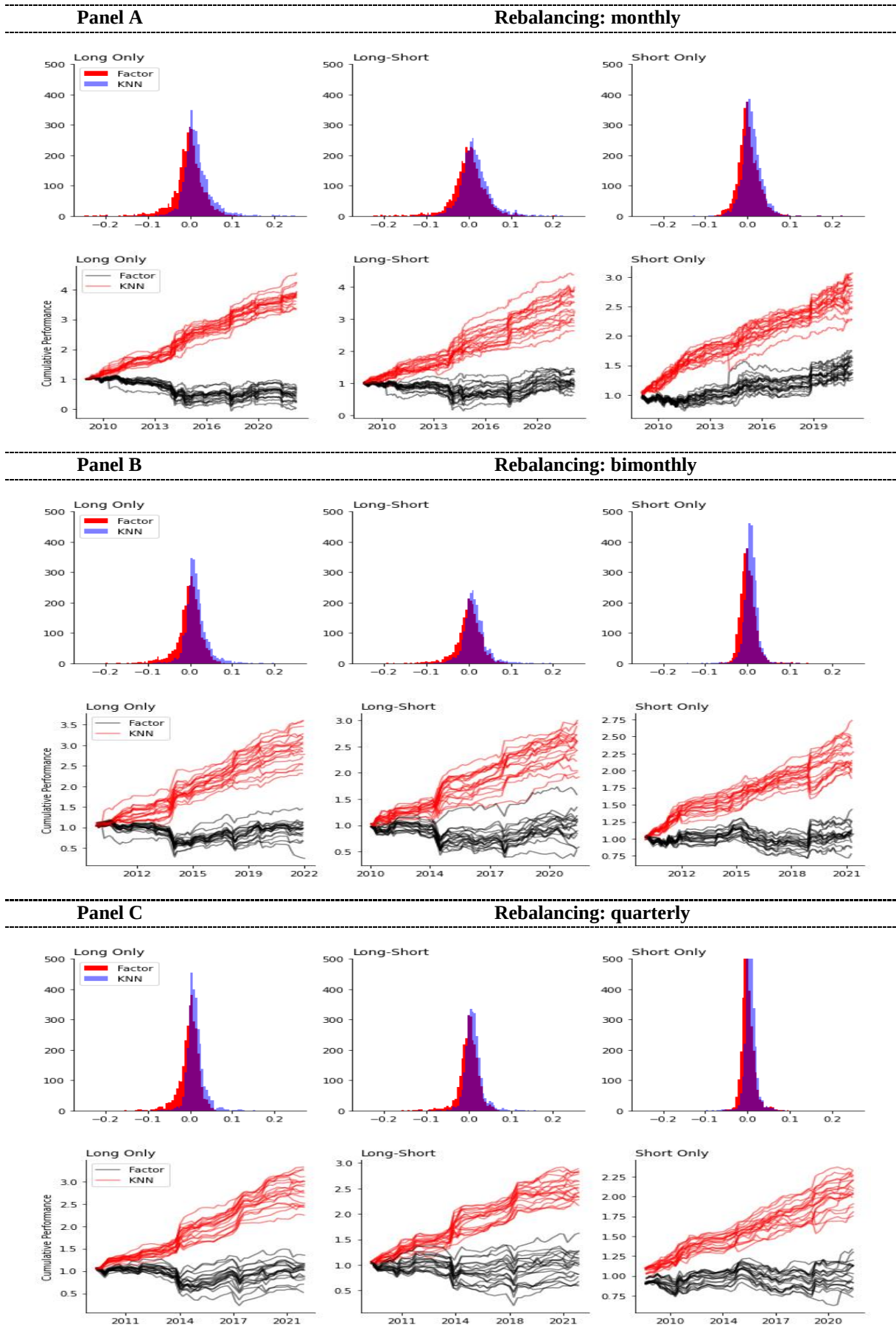


Table A4.M3-3: KNN vs 3m-momentum Factor.

The figures graphically compare (i) the distributions of the 3m-Momentum factor with the distributions of the timed factor based on KNN and (ii) the performance over time of the same 20 portfolios with and without timing

Appendix 4.M3.4 Support Vector Machine (SVM)

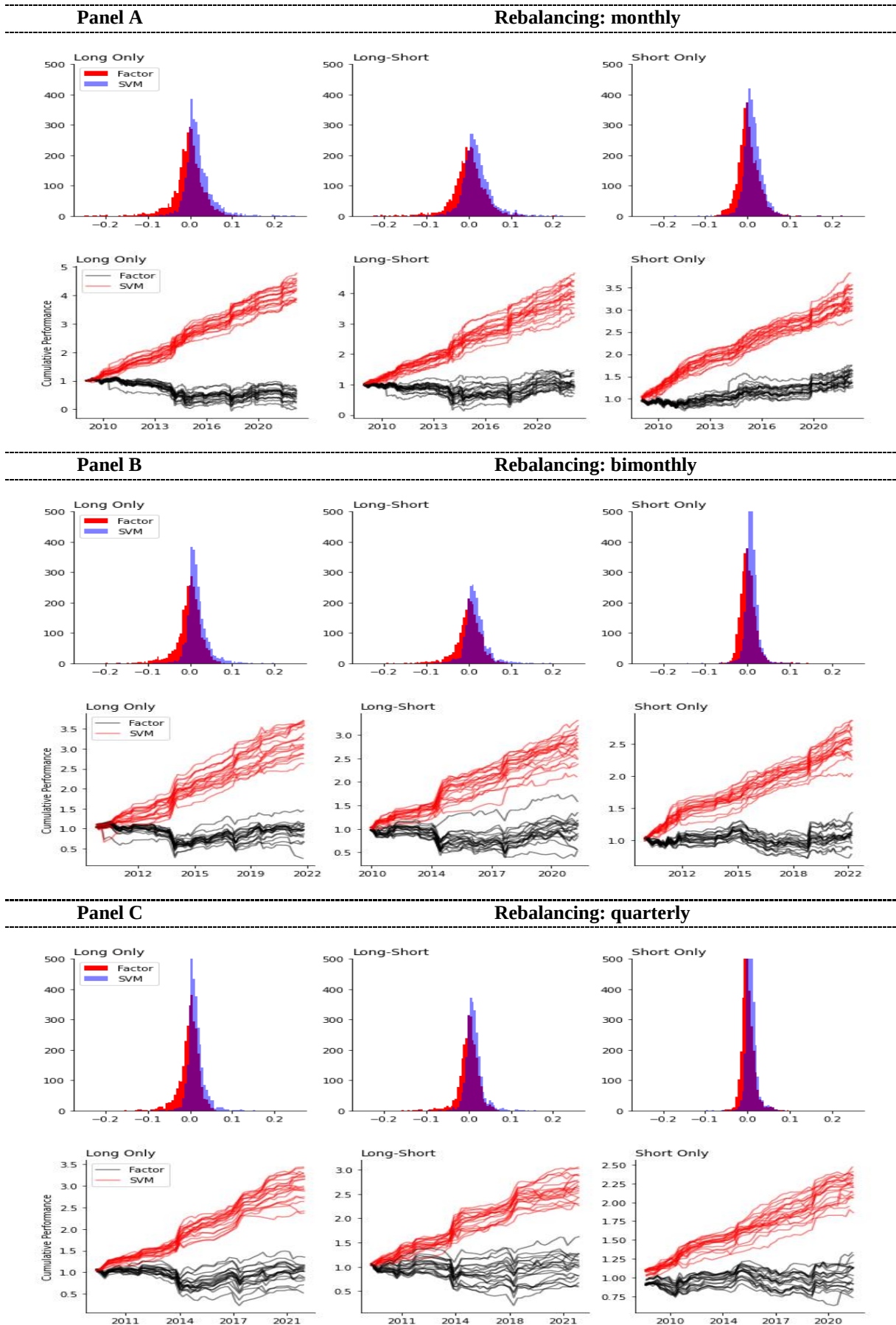


Table A4.M3-4: SVM vs 3m-momentum Factor.

The figures graphically compare (i) the distributions of the 3m-Momentum factor with the distributions of the timed factor based on SVM and (ii) the performance over time of the same 20 portfolios with and without timing

Appendix 4.M3.5 Random Forest (RF)

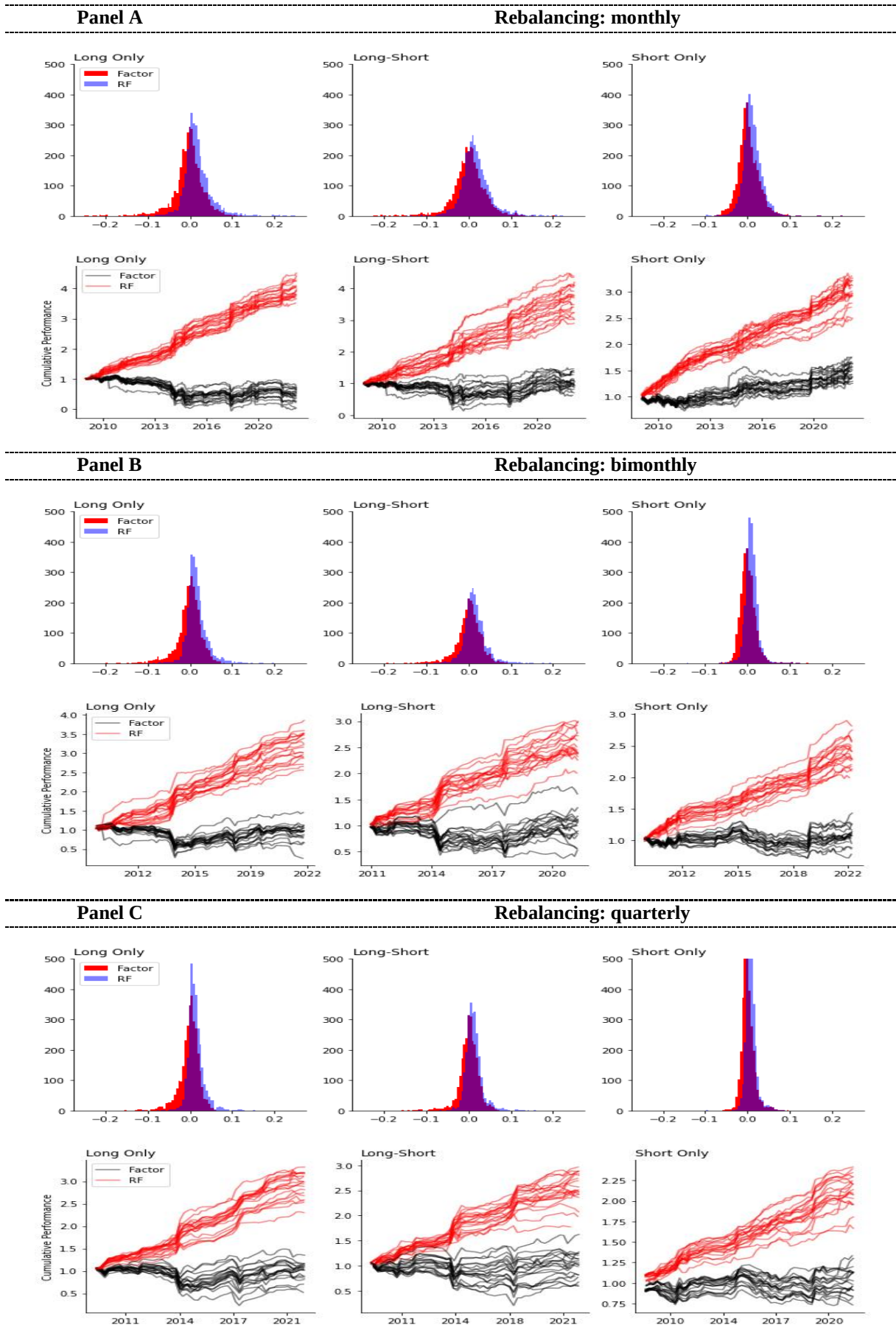


Table A4.M3-5: RF vs 3m-momentum Factor.

The figures graphically compare (i) the distributions of the 3m-Momentum factor with the distributions of the timed factor based on RF and (ii) the performance over time of the same 20 portfolios with and without timing

Appendix 4.M3.6 Recurrent Neural Network (RNN)

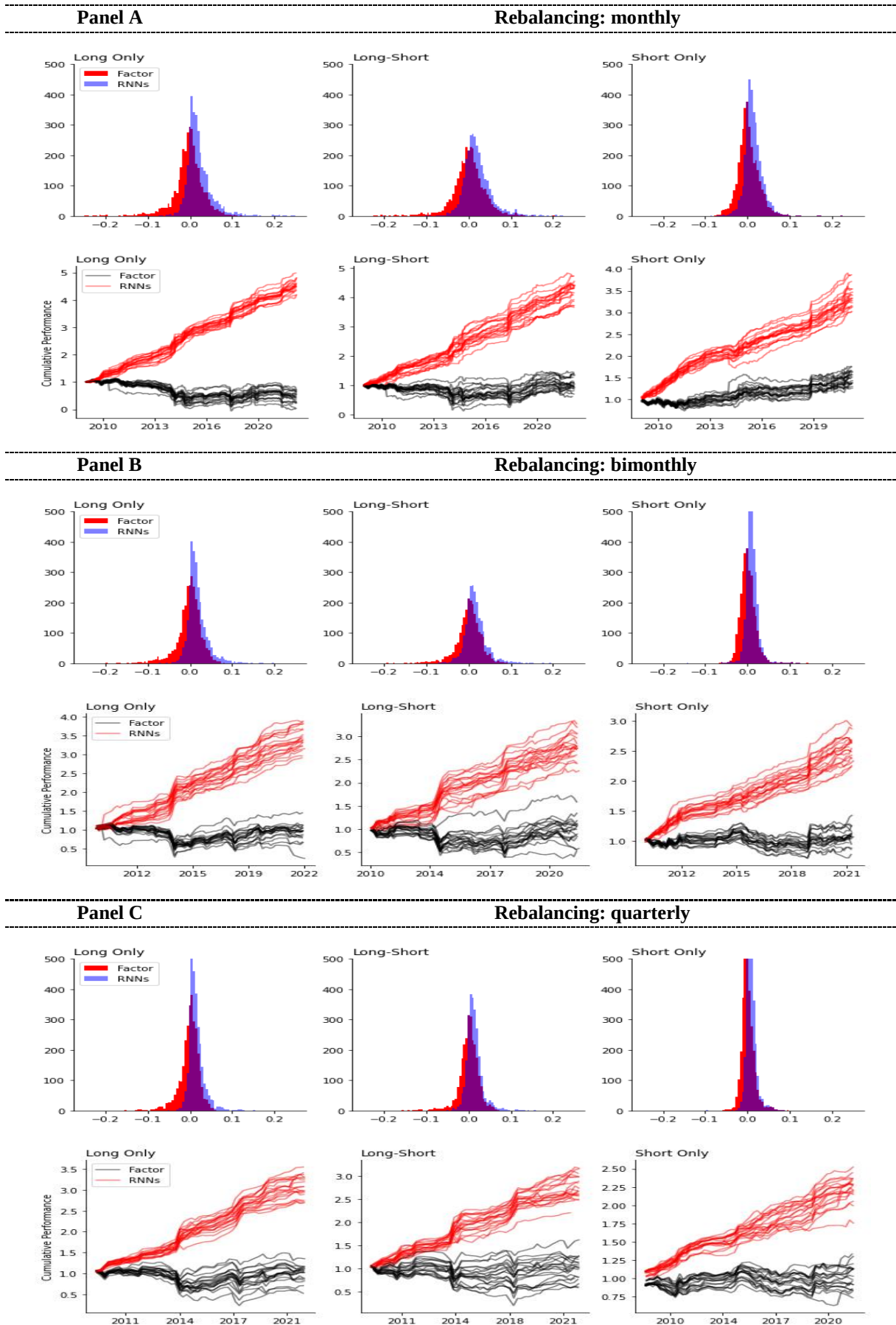


Table A4.M3-6: RNN vs 3m-momentum Factor.

The figures graphically compare (i) the distributions of the 3m-Momentum factor with the distributions of the timed factor based on RNN and (ii) the performance over time of the same 20 portfolios with and without timing

Appendix 4.M3.7 Long Short-Term Memory (LSTM)

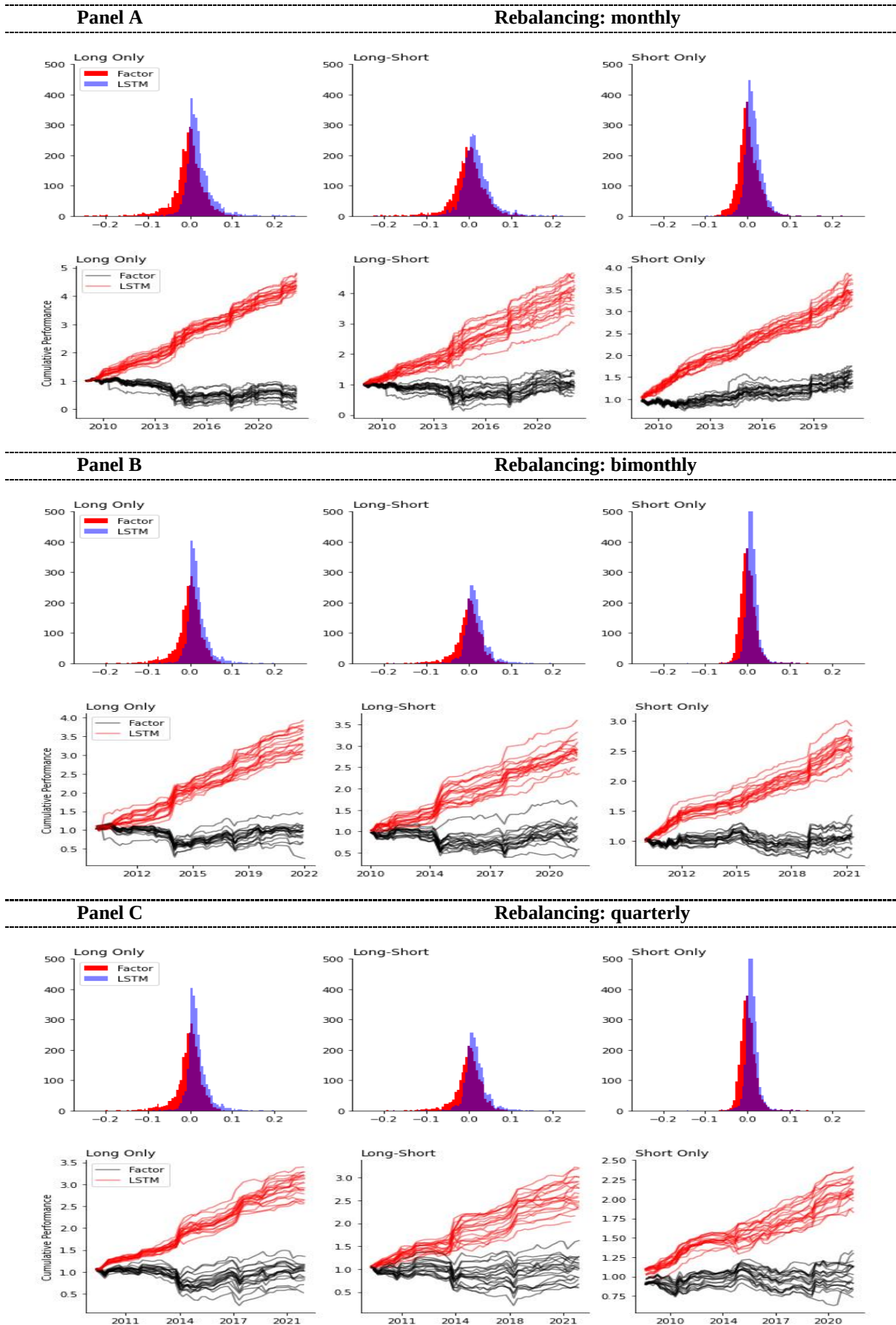


Table A4.M3-7: LSTM vs 3m-momentum Factor.

The figures graphically compare (i) the distributions of the 3m-Momentum factor with the distributions of the timed factor based on LSTM and (ii) the performance over time of the same 20 portfolios with and without timing

Appendix 4.M12.1. 12m-Momentum Factor

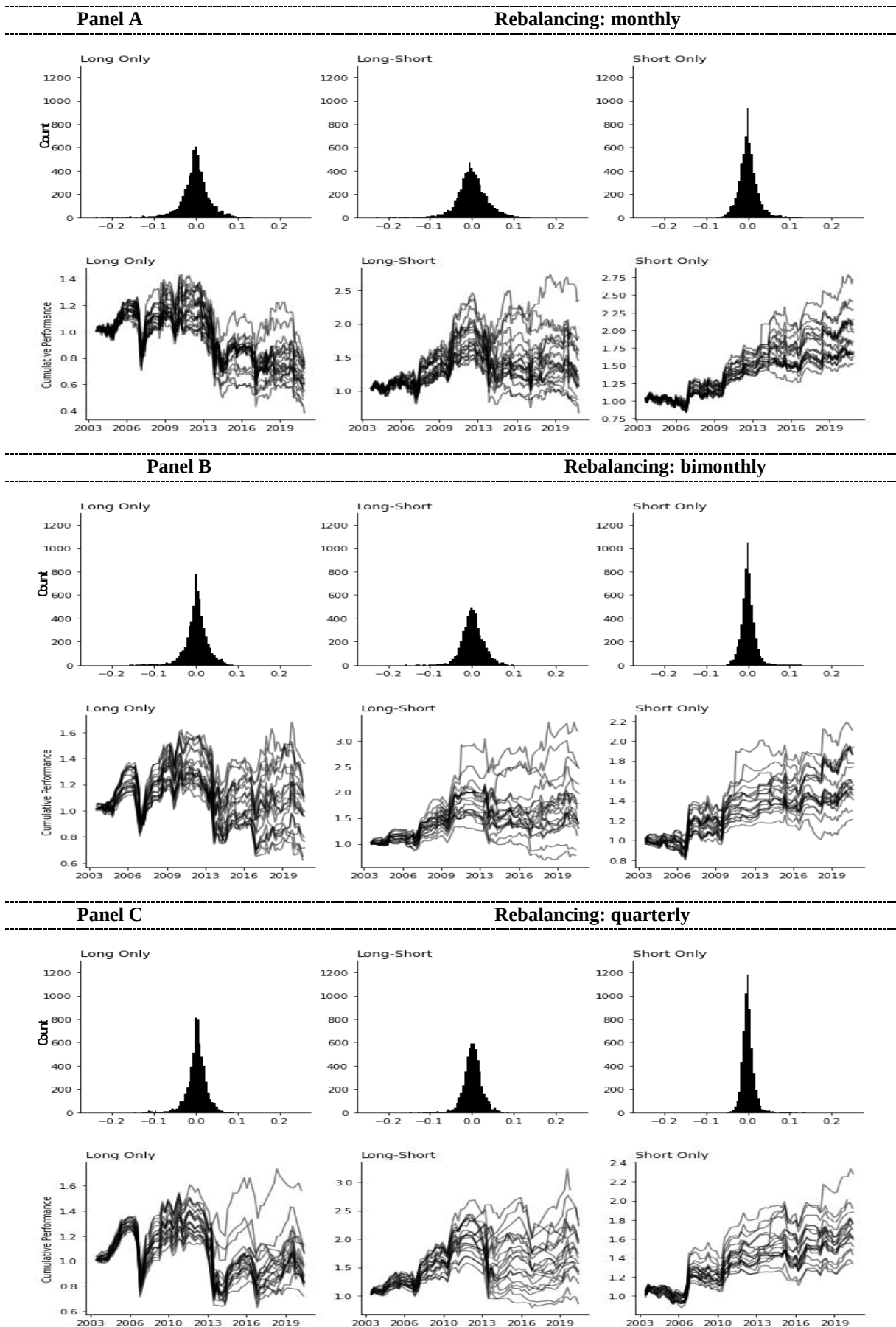


Table A4.M12-1: 12m-momentum Factor.

The figures graphically show (i) the distributions of the 12m-Momentum factor and (ii) the performance over time of 20 portfolios

Appendix 4.M12.2. Logistic Regression

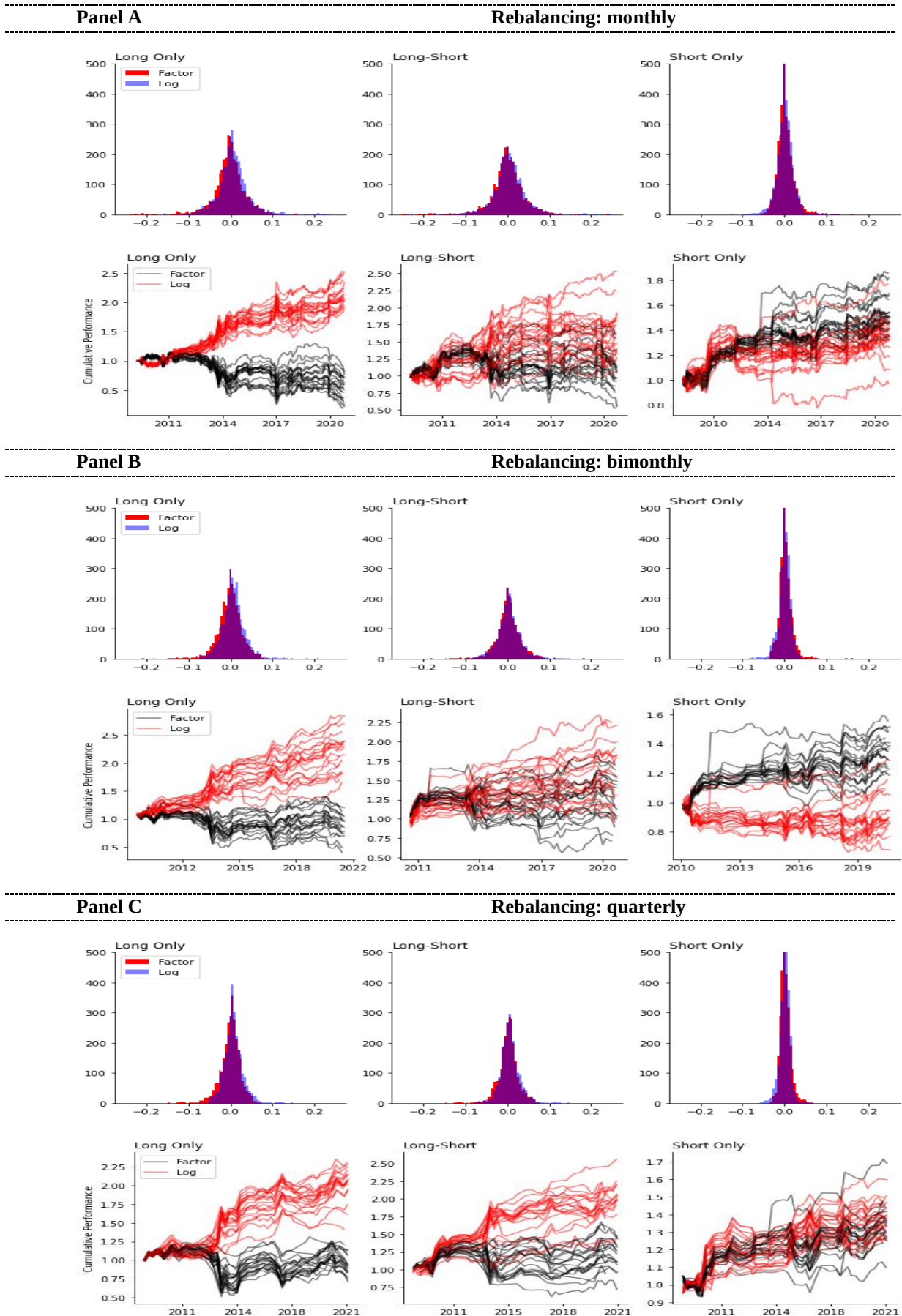


Table A4.M12-2: Logistic Regression vs 12m-momentum Factor.

The figures graphically compare (i) the distributions of the 12m-Momentum factor with the distributions of the timed factor based on logistic regression and (ii) the performance over time of the same 20 portfolios with and without timing

Appendix 4.M12.4 K-Nearest Neighbors (KNN)

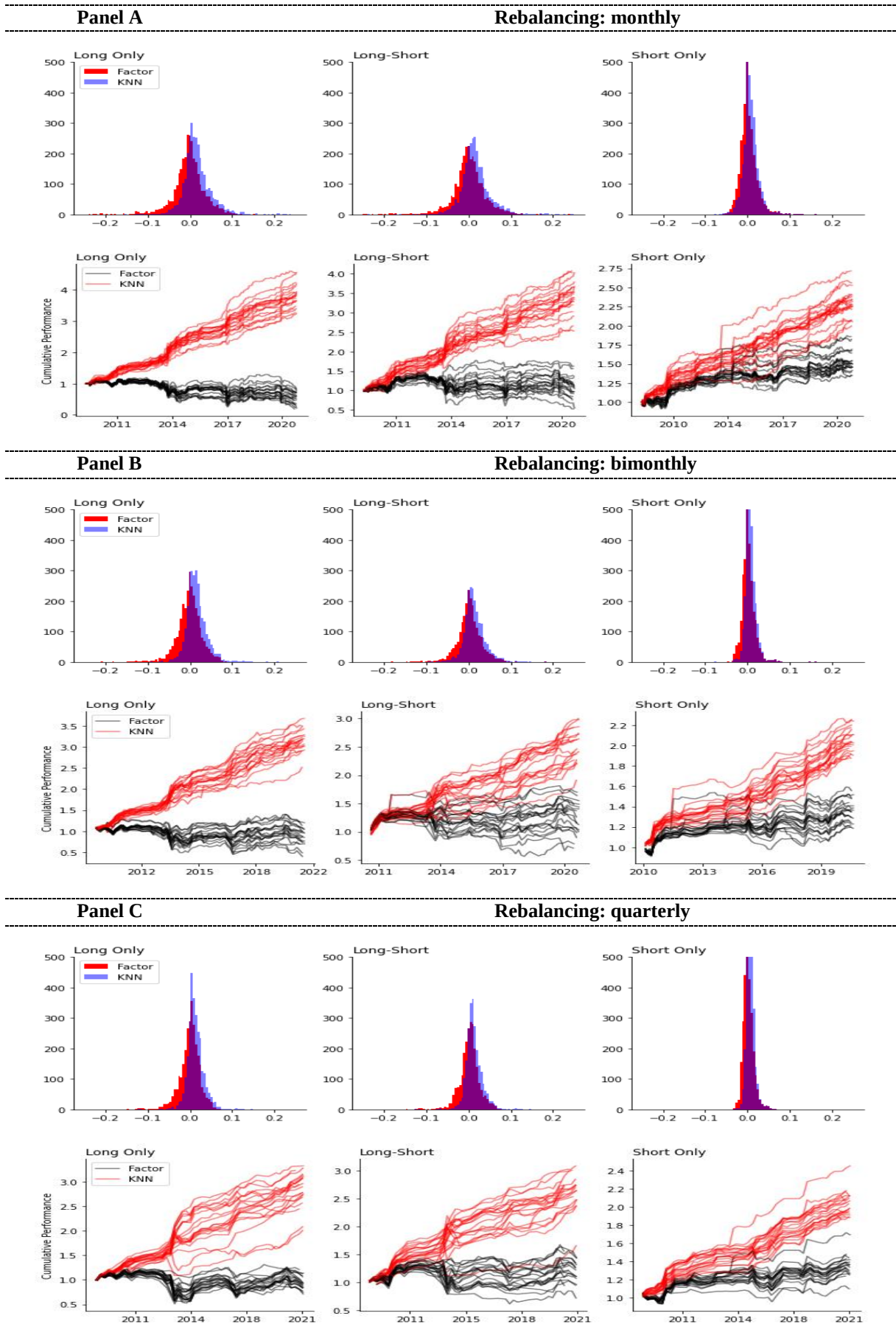


Table A4.M12-3: KNN vs 12m-momentum Factor.

The figures graphically compare (i) the distributions of the 12m-Momentum factor with the distributions of the timed factor based on KNN and (ii) the performance over time of the same 20 portfolios with and without timing

Appendix 4.M12.4 Support Vector Machine (SVM)

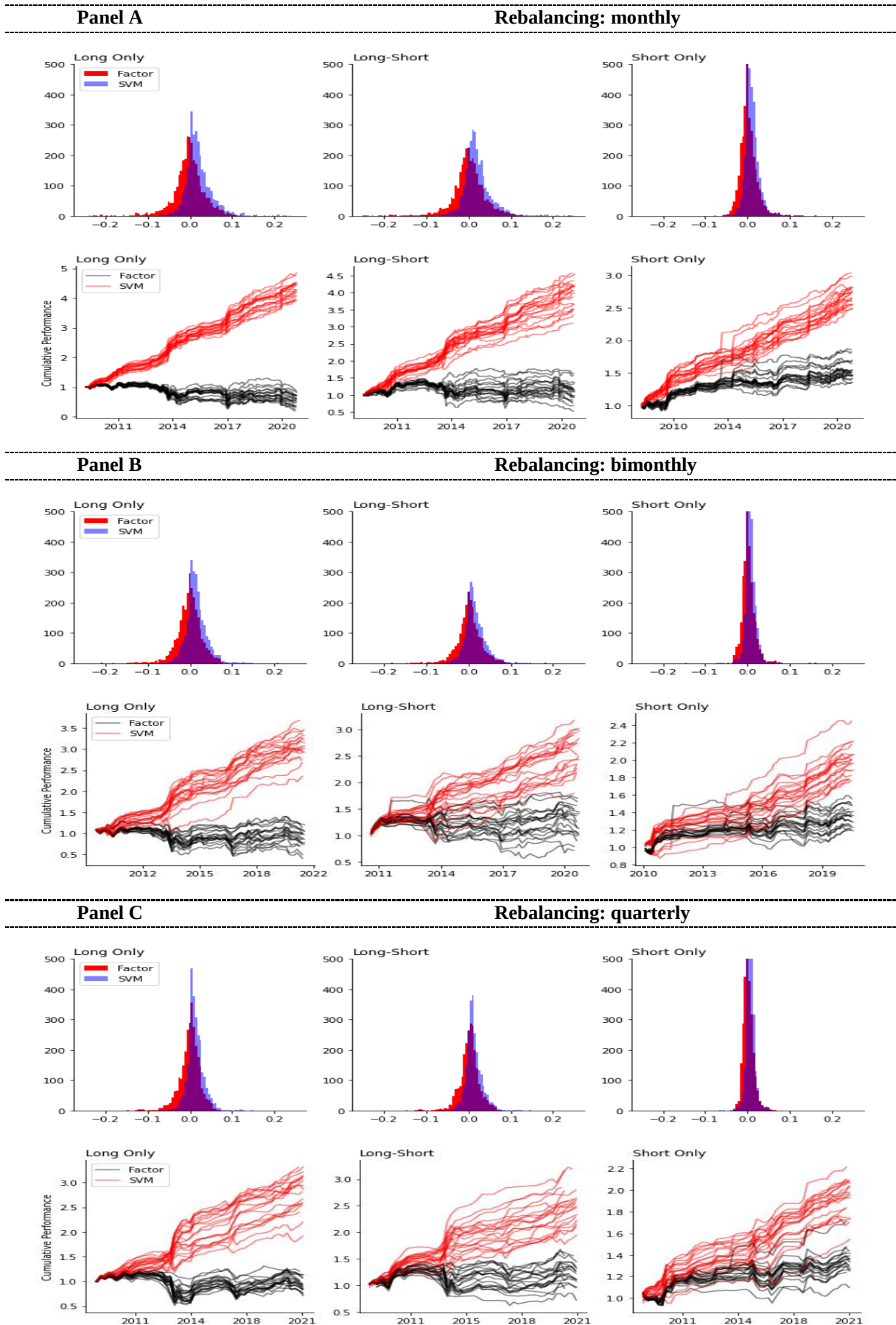


Table A4.M12-4: SVM vs 12m-momentum Factor.

The figures graphically compare (i) the distributions of the 12m-Momentum factor with the distributions of the timed factor based on SVM and (ii) the performance over time of the same 20 portfolios with and without timing

Appendix 4.M12.5. Random Forest (RF)

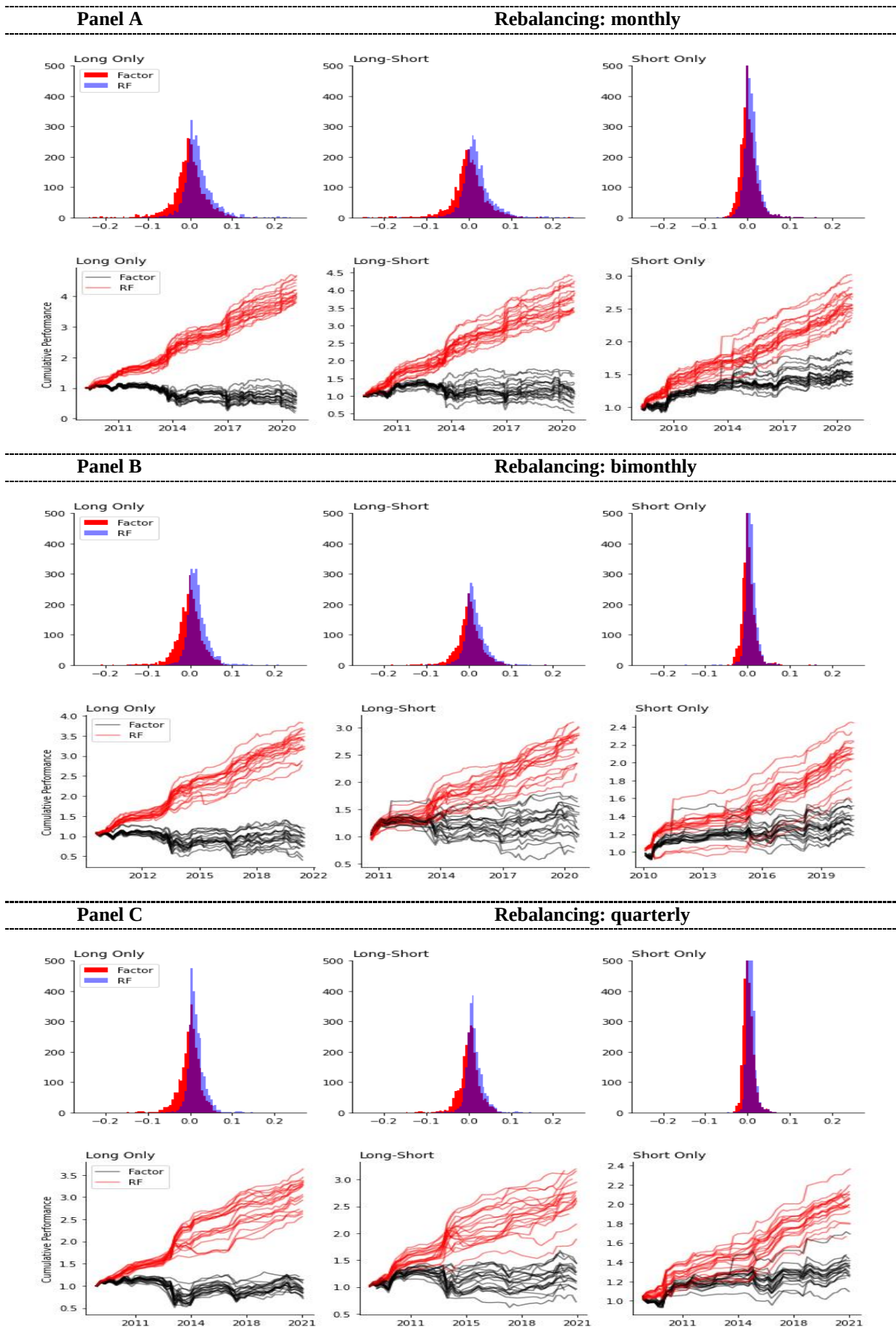


Table A4.M12-5: RF vs 12m-momentum Factor.

The figures graphically compare (i) the distributions of the 12m-Momentum factor with the distributions of the timed factor based on RF and (ii) the performance over time of the same 20 portfolios with and without timing

Appendix 4.M12.6. Recurrent Neural Network (RNN)

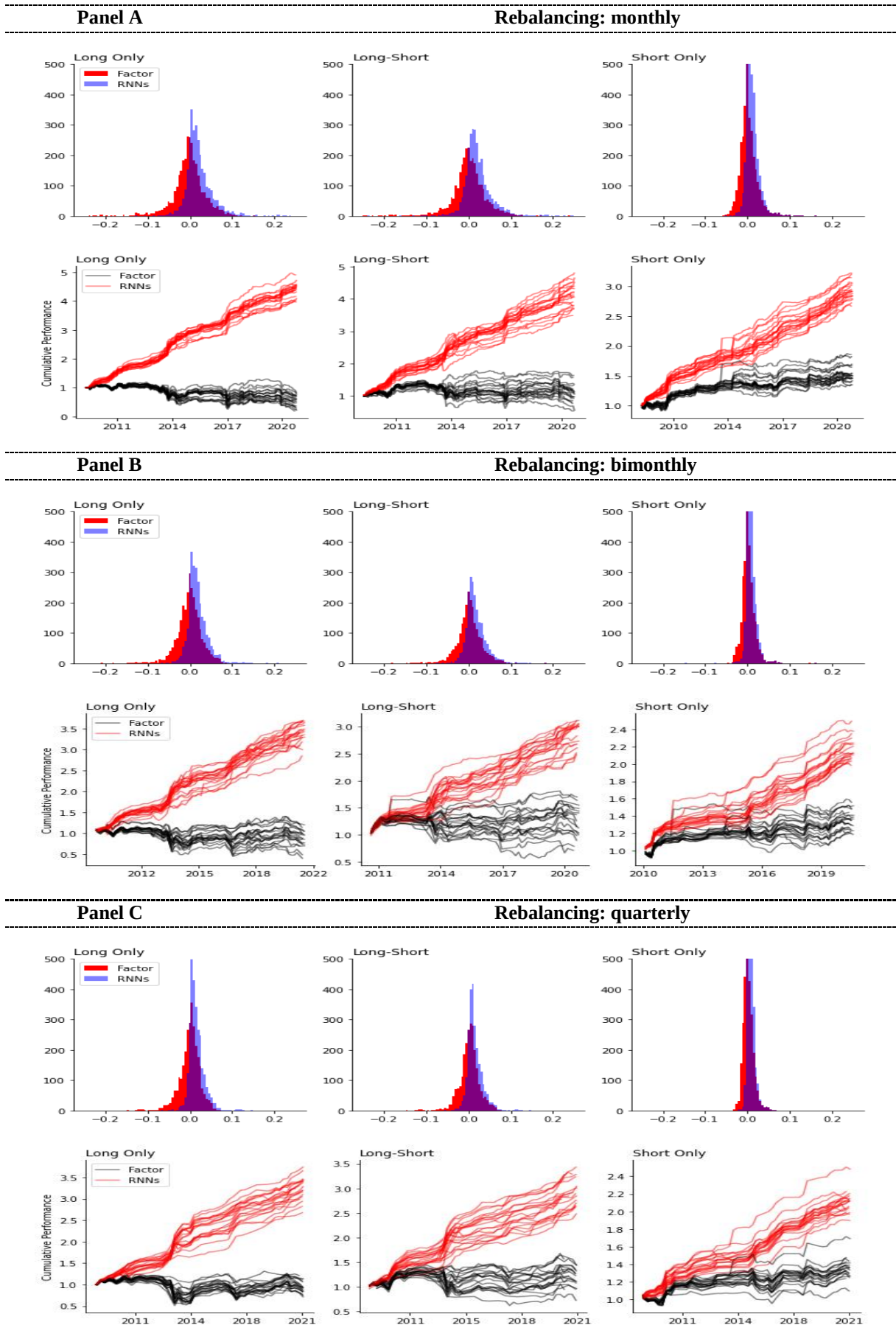


Table A4.M12-6: RNN vs 12m-momentum Factor.

The figures graphically compare (i) the distributions of the 12m-Momentum factor with the distributions of the timed factor based on RNN and (ii) the performance over time of the same 20 portfolios with and without timing

Appendix 4.M12.7 Long Short-Term Memory (LSTM)

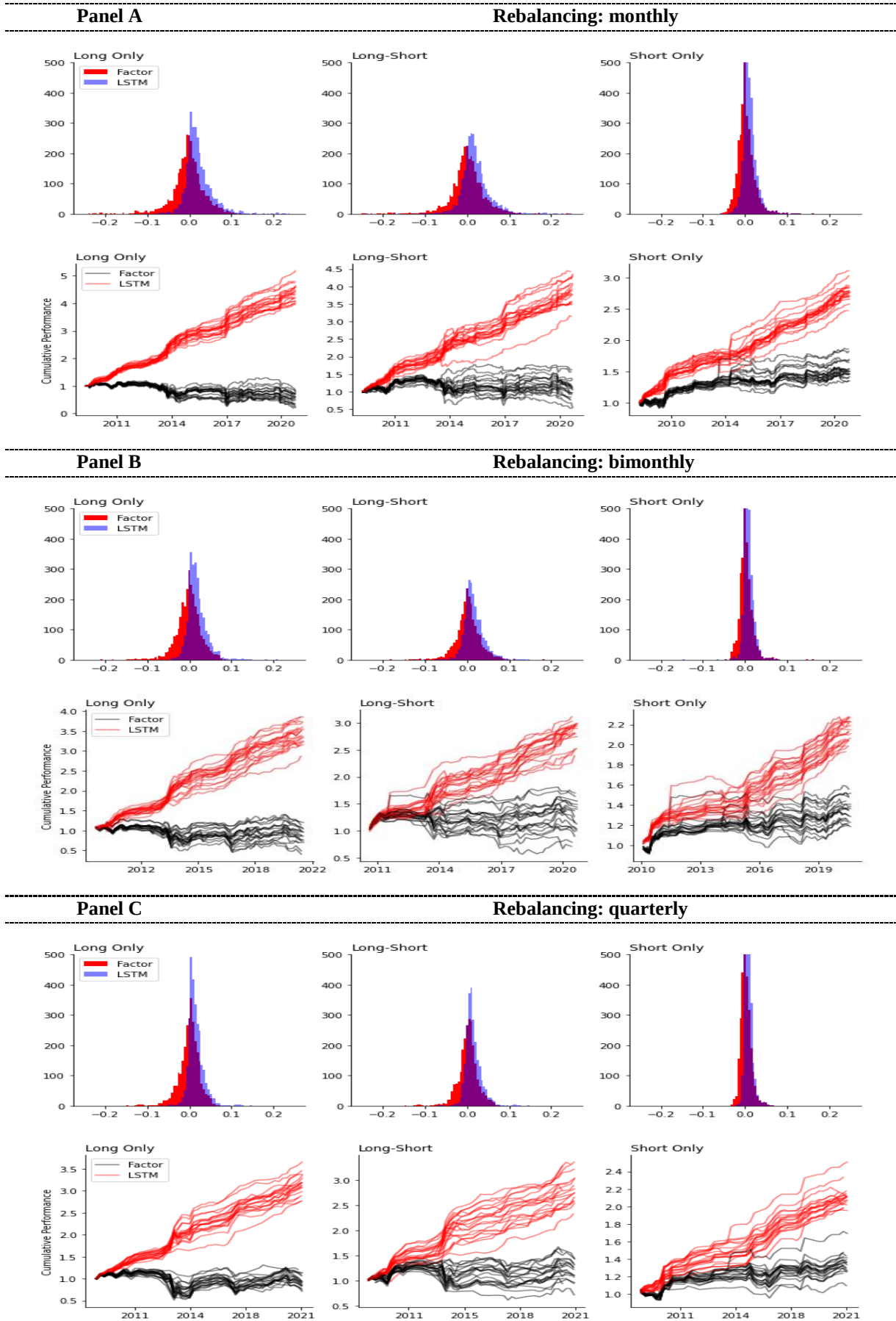


Table A4.M12-7: LSTM vs 12m-momentum Factor.

The figures graphically compare (i) the distributions of the 12m-Momentum factor with the distributions of the timed factor based on LSTM and (ii) the performance over time of the same 20 portfolios with and without timing

Appendix 5: Complements

Description: This appendix presents different complementary tables and graphics.

Table A5.1: List of Currencies.

Table A5.2: Logistic regression parameters for portfolios with monthly holdings.

Figure A5.1: 3m-momentum Factor Currencies.

Figure A5.2: 12m-momentum Factor Currencies.

AED United Arab Emrates Dirham	HRK Croatian Kuna	PHP Phillipinian Peso
ARS Argentinian Peso	HUF Hungarian Forint	PKR* Pakistan Rupee
AUD Australian Dollar	IDR Indonesian Rupee	PLN Polish Zloty
BGN Bulgarian Lev	ILS Israel New Shekel	QAR Qatar Rial
BRL Brazilian Real	INR Indian Rupee	RON Romanian New Lei
BWP* Botswana Pula	ISK* Iceland Krona	RSD Serbian Dinar
CAD Canadian Dollar	JOD* Jordan Dinar	RUB Russian Rouble
CHF Swiss Franc	JPY Japanese Yen	SEK Sweden Krona
CLP Chilian Peso	KES Kenya Schilling	SGD Singapore Dollars
CNH Chinese Yuan/Renminbi	KRW Korean Won	THB Thailand Baht
CNY* Chinese Yuan/Renminbi	KWD Kuwait Dinar	TND Tunisian Dinar
COP Colombia Peso	KZT* Kazakhstan Tenge	TRY Turkish New Lira
CZK Czech Koruna	MAD Marocco Dirham	TWD Taiwan Dollar
DKK Denmark Krone	MXN Mexican Peso	UAH Ukraine Hryvnia
EGP* Egypt Pound	MYR Malaysian Ringgit	UGX* Uganda Shilling
EUR Euro	NOK Norway Kroner	VND Vietna Dong
GBP Great Britain Pound	NZD New Zealand Dollar	ZAR South African Rand
GHS Ghana New Cedi	OMR Oman Rial	ZMW* Zambian Kwacha
HKD Hong Kong Dollar	PEN Peru Nuevo Sol	

Table A5.1: List of Currencies.

* No REER for the corresponding country/currency was found. Those currencies were not taken into account when forming the value factor.

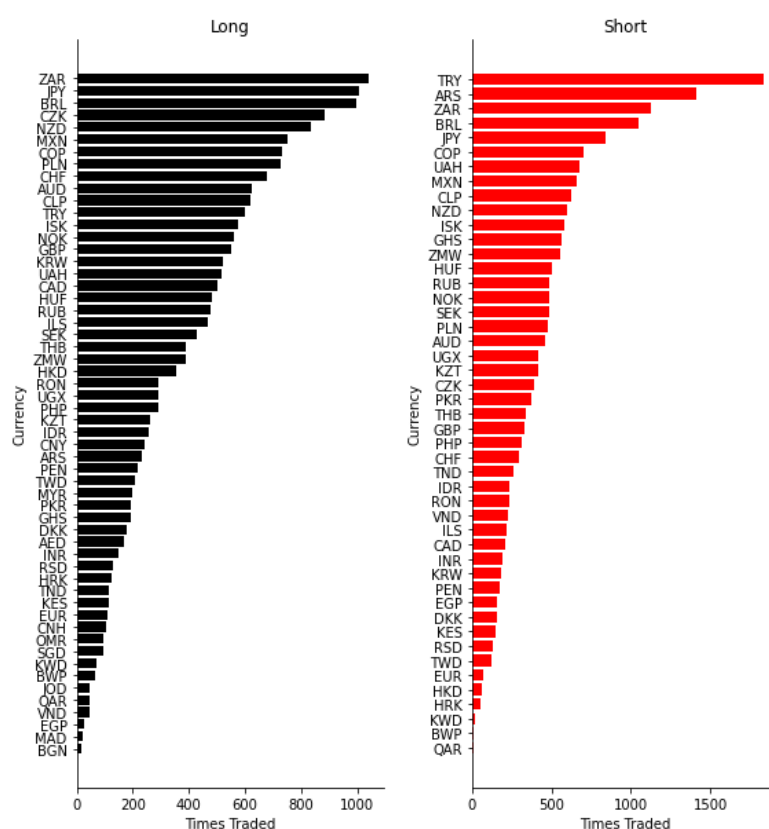


Figure A5.1: 3m-momentum Factor Currencies.

The data are for the period 02.01.2004 - 04.11.2022

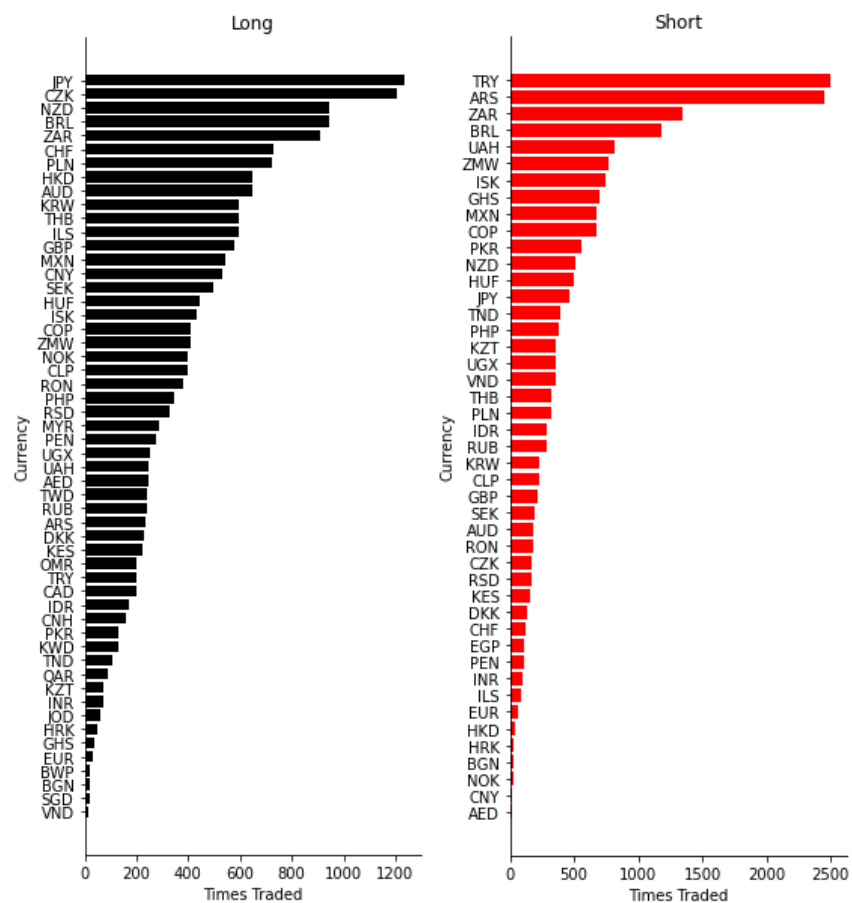


Figure A5.2: 12m-momentum Factor Currencies.
The data are for the period 02.01.2004 - 04.11.2022

	Value			Carry			1m-Mom			3m-Mom			12m-Mom		
	long	long/short	short	long	long/short	short	long	long/short	short	long	long/short	short	long	long/short	short
Intercept	-5.086	19.173***	24.019***	-1.12	-8.4*	-16.1***	8.421**	5.458 (.)	-2.441	8.553**	5.272 (.)	-6.546*	-12.594***	-8.183*	8.163*
REER INR	0.009	-0.035***	-0.036***	0.001	-0.02	0.01	0.004	0.005	0.012 (.)	0.008	-0.002	-0.004	0.002	0.039***	0.041***
REER CNY	0.002	-0.043**	-0.053***	0.04**	0.06***	0.07***	-0.062***	-0.031**	0.028**	-0.07***	-0.028**	0.04***	0.048***	0.02 (.)	-0.04***
REER EUR	0.05***	-0.018	-0.062***	-0.05***	0.01	0.05***	-0.037***	-0.025	0.002	-0.025*	-0.022*	0.001	0.006	-0.004	-0.018 (.)
REER JPY	-0.009	-0.01 (.)	-0.002	0.04***	0.04***	0.003	-0.005	-0.003	0	-0.015**	0.001	0.005	0.01*	0.008	-0.006
REER USD	0.002	-0.055***	-0.057***	-0.01	-0.01	0.006	0.027***	0.003	-0.018**	0.04***	0.016*	0.012	0.051***	0.01	-0.061***
VIX	-0.016*	-0.002	0	0.04***	0.04***	-0.002	0.02**	0.026 ***	-0.008	-0.011 (.)	-0.006	-0.006	-0.039***	-0.019	0.031***
BCOM	0.002	-0.024***	-0.031***	0.01**	0.01**	0.02	-0.013***	-0.01 ***	0.004 (.)	-0.014***	-0.012***	0.006*	0.015***	0.01	-0.007*
G10 FX Vola	0.087***	-0.122***	-0.148***	-0.09**	-0.02	0.08***	0.039	0.001	0.002	0.06*	-0.041 (.)	0.033	0.053*	0.045 (.)	0.077***
TED Spread	-0.005**	0.006***	0.008***	-0.003*	0.004*	0.006***	-0.004**	0	0.001	-0.008***	0	0.006***	0.002	-0.005***	-0.002
MOVE	-0.006**	0.009***	0.015***	-0.01**	-0.01***	-0.01***	0.005*	0.007**	0.001	-0.004 (.)	0.006*	0.001	0.003	0.008***	-0.002
Put/Call	-0.738*	-0.738*	-0.027	0.24	1.2**	0.3	-0.425	-0.332	-0.38	0.295	-0.005	0.036	-0.125	-0.206	-0.632*
NFCI	-0.086	-0.151	0.07	-0.12	-0.9***	-0.6***	0.168	-0.25 (.)	-0.112	0.915***	0.064	-0.617***	0.289*	0.279 (.)	-0.304*

Table A5.2: Logistic regression parameters for portfolios with monthly holdings.

The significance codes are given as follows:

*** 0.001, ** 0.01, * 0.05, (.) 0.1